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Abstract

Bargaining power in vertical channels depends critically on the "disagreement profit" or the opportunity cost to each player should negotiations fail. In a multiproduct context, disagreement profit depends on the degree of substitutability among the products offered by the downstream retailer. Horn and Wolinsky (1988) use this fact to argue for the clear importance of complementarity relationships on bargaining power. We develop an empirical framework that is able to estimate the effect of retail complementarity on bargaining power, and margins earned by manufacturers and retailers in the French soft drink industry. We show that complementarity increases the strength of retailers' bargaining position, so their share of the total margin increases by almost 28% relative to the no-complementarity case.

keywords: bargaining power, complementary goods, Nash-in-Nash equilibrium, retailing, soft drinks, vertical relationships

JEL Codes: D43, L13, M31

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1 Introduction

Empirical models of vertical bargaining power rely critically on estimates of how consumers respond to changes in prices in the downstream, or consumer, market. Typically, these models address retail purchases from only one category at a time (Villas-Boas and Zhao 2005; Villas-Boas 2007), whereas consumers tend to buy products by the shopping basket (Manchanda, Ansari, and Gupta 1999; Kwak, Duvvuri, and Russell 2015). Within a single category, the choices – different brands, for example – are plausibly all substitutes for each other. When buying multiple categories at a time, however, the purchase is likely to consist of a mix of substitutes and complements. In a theoretical treatment of this setting, Horn and Wolinksy (1988) show that when wholesale prices are negotiated between suppliers and downstream buyers, differences in how consumers respond to price changes can alter the nature of the bargaining outcome qualitatively for the upstream firms. While the potential for a complex pattern of substitutability and complementarity among items in the shopping basket may be relatively inconsequential if the items are from different manufacturers, the implications for vertical relationships between retailers and manufacturers cannot be ignored. In this research, we examine the importance of complementarity among retail grocery products for bargaining power between retailers and manufacturers.

With the global consolidation of food production in fewer and fewer hands, some manufacturers may be responsible for items in several categories in a typical shopping basket. We argue that this observation may have important implications for the balance of bargaining power between manufacturers and retailers in the food supply chain. Namely, when downstream firms sell complementary goods, an upstream supplier has less bargaining power than if products downstream are substitutes because the cost of not arriving at an agreement is higher for the supplier. Why? Because retailers are interested in category sales and manufacturers are interested in selling only their brands. When a retailer cannot sell a particular brand, it will sell another, while if a manufacturer selling to multiple retailers loses a distribution contract, the lost sales cannot be replaced as easily. If the manufacturer sells items in substitute categories – ketchup and mustard, for instance – the effect may not be substantial as lost sales can be regained elsewhere. However, if the manufacturer sells complementary goods – potato chips and dip, for instance – the effect of losing sales from a dropped brand in one category will be amplified by losses in the other. Therefore, the opportunity cost of arriving at an agreement, which is manifest in the difference between the current and disagreement profits, is higher for the manufacturer than the retailer. Because retail bargaining power is the mirror of manufacturer power, we expect retailer bargaining power to be higher when goods are complements.

It is well understood that complementarity affects pricing strategies among retailers downstream. Rhodes (2015) and Smith and Thomassen (2012) argue that internalizing cross-product pricing effects on the intra-retailer margin with complementarity leads to lower retail prices as retailers have an incentive to drive volume rather than margin. On the other hand, Richards and Hamilton (2016) show that complementarity on the inter-retailer margin is associated with anti-competitive effects and is a source of market power for retailers. However, none of these studies focus on vertical relationships between multi-product retailers and manufacturers.

The increasing prevalence of highly granular data on consumer purchases, whether from frequent shopper cards or from household panel data sets, both highlights the importance of examining shopping-basket purchases, and makes structural models of multi-product purchasing behavior possible. By observing purchases on each shopping-occasion basis, we have a better understanding of how consumers combine products in a shopping list. Namely, previous research shows that consumers tend to make multiple discrete purchases (Dube 2004, 2005; Richards, Pofahl, and Gomez 2012) and tend to purchase some pairs of products at the same time, for reasons other than traditional price-based complementarity reasons (Song and Chintagunta 2007; Mehta 2007). In this paper, we develop a new model of retail demand that explicitly recognizes the importance of these two features of consumer-level purchase behavior.

Our demand model is of the multi-variate logit (MVL) class, in which consumers are assumed to make discrete choices among baskets of items. Because each item can reside in one of many different baskets, the choices cannot be described by a traditional logit model. Russell and Peterson (2000) show how the auto-logistical model from spatial econometrics (Besag 1974) can be used in a shopping-basket model environment to consistently estimate demand elasticities that include a full-range of possibilities, from complementarity to substitutability, and independence in demand. Further, because the estimating model assumes a closed-form, Kwak, Duvvuri, and Russell (2015) show that it can be used to inform a wide range of practical issues in structural demand modeling. For this paper, we demonstrate how the implicit assumption of strict-substitutability from more usual logit models of demand can impart significant bias to bargaining power estimates in an environment in which demand relationships are likely to be more general.

Structural models of vertical relationships between retailers and manufacturers are, by now, reasonably well understood. Assuming Bertrand-Nash rivalry among downstream retailers, the solution to the Nash bargaining problem between retailers and manufacturers yields a single parameter that describes the share of the total margin that is appropriated by either the manufacturer or the retailer, depending on the relative bargaining strength of either party (Draganska, Klapper, and Villas-Boas 2010).[1] While others investigate structural factors that may influence the degree of bargaining power possessed by either side (Meza and Sudhir 2010; Haucap et al. 2013; Bonnet and Bouamra-Mechemache 2016), the role of demand-interrelationships among downstream retailers is not well understood, despite the clear theoretical importance it plays in the likely outcome of any negotiation (Bulow et al. 1985; Binmore, Rubinstein and Wolinsky 1986; Horn and Wolinsky 1988).[2] In this paper, we show that the structure of demand, namely whether products are substitutes or

[1] Misra and Mohanty (2006) develop a similar approach to modeling vertical relationships in which prices are the result of a Nash bargaining equilibrium, and show that their model fits the data better than existing empirical models in two different grocery categories.

[2] Iyer and Villas-Boas (2003) and Feng and Lu (2013a,b) apply a Nash bargaining model to vertical relationships in a supply-chain context.

complements, can have dramatic effects on estimated bargaining-power parameters.[3]

We test our hypothesis using data on multi-category soft drink purchases among households in France. While a discrete-choice model of category incidence would restrict all pairs of categories to be substitutes, we find that complementarity is more common than subtitutability at the brand level. When we condition equilibrium wholesale prices on our MVL demand estimates, we find that complementarity is associated with less manufacturer bargaining power and greater retail bargaining power. When products sold by one manufacturer are complements downstream, the disagreement profit, which is the amount earned if the parties fail to agree, is lower with complementarity than under strict substitutability. Lower disagreement profit implies a higher opportunity cost of agreeing. As a result, manufacturers are essentially more keen to arrive at a negotiated solution, so their bargaining power is lower. Our findings have broader implications for vertical relationships in any other industry in which powerful suppliers sell complementary products through oligopoly downstream retailers.

Our research contributes to both the theoretical literature on vertical relationships between suppliers and retailers, and the empirical literature on the nature of bargaining power in those relationships. While Horn and Wolinsky (1988) identify the mechanism that is likely to influence bargaining power in vertical relationships when products interact in the downstream market, their model is highly stylized, as it is framed in terms of an upstream duopoly and downstream duopoly firms. Our model, however, is able to accommodate more general oligopoly relationships among firms both upstream and downstream. In terms of the empirical bargaining power literature, we show how the single-category model of Draganska, Klapper, and Villas-Boas (2010) can be extended to a more general, multi-category demand framework, and show that doing so can have dramatic effects on the nature of the equilibrium bargaining solution that results.

In the next section, we describe our multi-category demand model, and how it is able to

[3]Dukes, Gal-Or, and Srinivasan (2006) show that differences among retailers can be important in influencing bargaining power in the vertical channel. Our empirical model captures retailer heterogeneity.

capture complementarity in household-level beverage purchases. The Nash bargaining power model is presented in the third section, where we show how our core hypotheses regarding complementarity and bargaining power are tested. We describe the data from our French soft-drink example in the fourth section, and present some stylized facts that suggest how a shopping-basket approach is both appropriate and necessary in data such as ours. We present and interpret the demand and pricing model results in a fifth section, while the final section concludes, and offers some implications for settings beyond our retail grocery example.

2 Empirical Model of Multi-Category Pricing

2.1 Overview

We examine the role of complementarity in bargaining power using a structural model of multi-category retail demand, and vertical pricing relationships between beverage manufacturers and retailers in France. Our model is innovative in that the demand component describes relationships among beverages found in a typical shopping-basket, unlike most conventional analyses in this area (Draganska, Klapper, and Villas-Boas 2010). Our demand model is multi-category in nature in that it recognizes the fact that items are purchased through a discrete-choice data generating process, but will nearly as often be complementary as they are substitutes with other items in the basket. When a retailer sells items from the same manufacturer that are likely to be complements, the implications for bargaining power in the vertical channel may be dramatic. Our model is structural in that we estimate equilibrium pricing relationships in the vertical channel, conditional on the structure of retail demand (Villas Boas 2007; Bonnet and Dubois 2010; Bonnet and Bouamra-Mechemache 2016) across multiple product categories.

2.2 Model of Multi-Category Demand

We develop our empirical model of multi-category choice and local-content demand from a single utility function, in the sense that consumers are assumed to maximize utility in choosing which categories to buy from on each trip to each store, $r = 1, 2, ..., R$. For clarity, we suppress the store subscript until we describe the equilibrium vertical pricing game below. Consumers $h = 1, 2, 3, ..., H$ in our model select items from among $i = 1, 2, 3, ..., I$ categories, c_{iht}, in assembling a shopping basket, or bundle, $\mathbf{b}_{ht} = (c_{1ht}, c_{2ht}, c_{3ht}, ..., c_{Iht})$ on each trip, t. Define the set of all possible bundles $\mathbf{b}_{ht} \in \mathbf{B}$ and the set of categories $i, j \in I$. We focus on purchase incidence, or the probability of choosing items from a particular category on each trip to the store, and regard the brand of the chosen item as an attribute of the choice. We assume consumers purchase only one brand within each category in order to remain consistent with the literature. We further assume consumers choose categories in order to maximize utility, U_{ht}, and follow Song and Chintagunta (2006) in writing their utility in terms of a discrete, second-order Taylor series approximation to an arbitrary utility function. Utility is written as:

$$\begin{aligned} U_{ht}(\mathbf{b}_{ht}) &= V_{ht}(\mathbf{b}_{ht}) + \varepsilon_{ht} \qquad (1) \\ &= \sum_{i \in I} \pi_{iht} c_{iht} + \sum_{i \in I} \sum_{j \in I} \theta_{ijh} c_{iht} c_{jht} + \varepsilon_{ht}, \end{aligned}$$

where π_{iht} is the baseline utility for category i earned by household h on shopping trip t , c_{iht} is a discrete indicator that equals 1 when category i is purchased, and is 0 otherwise, ε_{ht} is an error term that is Gumbel distributed, and iid across households and shopping trips, and θ_{ijh} is a household-specific parameter that captures the degree of interdependence in demand between categories i and j, such that if $\theta_{ijh} < 0$, the categories are substitutes, if $\theta_{ijh} > 0$, the categories are complementary, and if $\theta_{ijh} = 0$, the pair of categories are independent in demand. For example, we would expect to find $\theta_{ijh} > 0$ for ketchup and hamburger, but $\theta_{ijh} < 0$ for ketchup and bbq sauce, and $\theta_{ijh} = 0$ for ketchup and laundry detergent. In order to ensure that the model is identified, it is necessary that all $\theta_{ii} = 0$ and that symmetry be imposed on the matrix of cross-purchase effects such that $\theta_{ijh} = \theta_{jih}, \forall i, j, h$ (Besag 1974, Cressie 1993, Russell and Petersen 2000).

The probability that a household purchases in a given category on a purchase occasion, or category incidence, depends on both perceived need, and marketing activities from the brands in the category (Bucklin and Lattin 1992, Russell and Petersen 2000). Because we seek to examine demand relationships, and pricing behavior, at the brand-and-retailer level, however, we extend the usual MVL specification to consider the demand for specific items within each category. We then capture interactions in a parsimonious way through the interaction terms given in (1).[4] Therefore, we write baseline utility for each brand (k), retailer (r), and category (i) as:

$$\pi_{ikrht} = \alpha_{ikr} + \beta_{ih}\mathbf{X}_{ikr} + \gamma_i \mathbf{Z}_h, \tag{2}$$

where α_{ikr} are fixed effects that control for the particular brand, k, that is purchased from retailer, r, in category i, $\mathbf{X}_{ik}$ is a matrix of category-specific marketing mix elements for each brand, and $\mathbf{Z}_h$ is a matrix of household attributes.[5] Household attributes affect perceived need, as measured by the rate at which a household consumes products in the category, which when combined with the frequency of category-purchase, determines the amount on hand (INV_h). We infer household inventory using methods that are standard in this literature (Bucklin and Lattin 1992). Namely, we calculate the category-consumption rate for each household by calculating their total purchases over the sample period, and divide by the total number of days in the data set. We then initialize inventory at the average consumption-rate at the start of the time-period for each household, and increment inventory upward with purchases, and downward each day by the average consumption rate. Need is also determined by more fundamental household factors such as the size of the household (HH_h), income level (INC_h), and education (EDU_h). Any state dependence in demand

[4] Conceptually, a fully-nested version of the MVL would be preferably, but proved to be empirically intractable.

[5] One brand each in the fruit juice and iced tea categories was offered in only one retailer, so brand effects could not be identified separately from retailer effects.

is assumed to be captured by the inventory variable as it reflects intertemporal changes in consumption behavior. Marketing mix elements at the brand-category level include the price of the individual items in each category (p_{ikr}), and an indicator of whether the item was on promotion during the purchase occasion at a particular retailer (PR_{ikr}).[6]

Each of the variables entering (2) represent sources of observed heterogeneity, whether at the item (brand / category / retailer) ($\mathbf{X}_{ikr}$) or household ($\mathbf{Z}_h$) levels. However, there is also likely to be substantial unobserved heterogeneity in household preferences and in attributes of the item that may affect incidence. Therefore, we capture unobserved heterogeneity in item preference by allowing for randomly-distributed category-interactions (θ_{ijh}) and item-level price-response (β_{pih}). Formally, therefore, we estimate:

$$\begin{aligned} \beta_{pih} &= \beta_{pi0} + \beta_{pi1}\nu_{i1}, \ v_{i1} \sim N(0, \sigma_1), \ \forall i, \qquad (3) \\ \theta_{ijh} &= \theta_{ij0} + \theta_{ij1}\nu_2, \ v_2 \sim N(0, \sigma_2), \end{aligned}$$

for the price-element of the marketing-mix matrix, and for each of the ij category-interaction parameters. By allowing for a general pattern of correlation among these parameters (Singh, Hansen, and Gupta 2005), we capture a primary source of coincident demand among categories. In other words, if households tend to be correlated in terms of their price sensitivity, then allowing for co-movements in demand due to price responsiveness will remove some element of randomness from the error term, leaving less variation to be explained by other factors. This extension to the MVL model, by incorporating random parameters into both the marketing-mix and category-interaction parameters is called the random-parameters MVL model, or RP-MVL.

With the error assumption in equation (1), the conditional probability of purchasing in each category assumes a relatively simple logit form. Following Kwak, Duvvuri, and Russell (2015), we simplify the expression for the conditional incidence probability by writing the cross-category purchase effect in matrix form, where: $\Theta_h = [\Theta_{1h}, \Theta_{2h}, ..., \Theta_{Nh}]$ and each Θ_{ih}

[6] The promotion indicator is inferred from the prices paid by each household. If the price paid is less than 90% of the previous price paid for that item, and the price rises back to the previous level on the next purchase occasion, then we infer that the purchase was made on promotion.

represents a column vector of the $I \times I$ cross-effect Θ_h matrix which is defined as:

$$\Theta_h = \begin{bmatrix} 0 & \theta_{12h} & \theta_{13h} & ... & \theta_{1Ih} \\ \theta_{21h} & 0 & & ... & \theta_{2Ih} \\ \theta_{31h} & \theta_{32h} & 0 & ... & \theta_{3Ih} \\ . & . & . & ... & . \\ . & . & . & ... & . \\ \theta_{I1h} & \theta_{I2h} & \theta_{I3h} & ... & 0 \end{bmatrix}, \tag{4}$$

so that the conditional utility of purchasing an item in category i is written as:

$$U_{ht}(c_{ikrht}|c_{jkrht}) = \pi'_{ht}\mathbf{b}_{ht} + \Theta'_{ih}\mathbf{b}_{ht} + \varepsilon_{ht}, \tag{5}$$

for the items i, k, r in the basket vector $\mathbf{b}_{ht}$. Conditional utility functions of this type potentially convey important information, and are more empirically tractable that the full probability distribution of all potential assortments (Moon and Russell 2008), but are limited in that they cannot describe the entire matrix of substitute relationships in a consistent way, and are not econometrically efficient in that they fail to exploit the cross-equation relationships implied by the utility maximization problem. To see this more clearly, we derive the estimating equation implied by the Gumbel error-distribution assumption, conditional on the purchases made in all other categories, c_{jht}. With this conditional assumption, the probability of purchasing an item from category $i = 1$ is written as:

$$\Pr(c_{1krht} = 1|c_{jkrht}) = \frac{[\exp(\pi_{1krht} + \Theta'_{1h}\mathbf{b}_{ht})]^{c_{1krht}}}{1 + \exp(\pi_{1krht} + \Theta'_{1h}\mathbf{b}_{ht})}, \tag{6}$$

and $\mathbf{b}_{ht}$ represents the basket vector. Estimating all I of these equations together in a system is one option, or Besag (1974) describes how the full distribution of $\mathbf{b}_{ht}$ choices are estimated together.

Assuming the Θ_h matrix is fully symmetric, and the main diagonal consists entirely of zeros, then Besag (1974) shows that the probability of choosing the entire vector $\mathbf{b}_{ht}$ is written as:

$$\Pr(\mathbf{b}_{ht}) = \frac{\exp(\boldsymbol{\pi}'_{ht}\mathbf{b}_{ht} + \frac{1}{2}\mathbf{b}'_{ht}\Theta_h\mathbf{b}_{ht})}{\sum\limits_{\mathbf{b}_{ht}\in\mathbf{B}}[\exp(\boldsymbol{\pi}'_{ht}\mathbf{b}_{ht} + \frac{1}{2}\mathbf{b}'_{ht}\Theta_h\mathbf{b}_{ht})]}, \tag{7}$$

where $\Pr(\mathbf{b}_{ht})$ is interpreted as the joint probability of choosing the observed combination of categories from among the 2^I potentially available from I categories.[7] Assuming the elements of the main diagonal of Θ is necessary for identification, while the symmetry assumption is required to ensure that (7) truly represents a joint distribution, a multi-variate logistic distribution, of the category-purchase events. Essentially, the model in (7) represents the probability of observing the simultaneous occurrence of I discrete events – a shopping basket – at one point in time. And, due to the iid assumption of the logit errors associated with each basket choice, the model in (7) implicitly assumes that the baskets are subject to the independence of irrelevant alternatives (IAA), but the categories within the basket are allowed to assume a more general correlation structure (Kwak, Duvvuri, and Russell 2015). Aggregating (7) over households then produces an expression for the probability of purchasing each basket, and each component brand, category, retailer combination captured by each basket.

Given the similarity of the choice probabilities to logit-choice probabilities, it is perhaps not surprising that the form of the elasticity matrix is also similar. Given the probability expression above, the marginal effect of a price change in brand k, category i, and retailer r, on the own-probability of purchase is written as:

$$\frac{\partial \Pr(c_{ikr})}{\partial p_{ikr}} = \beta_{pih} \Pr(c_{ikr})(1 - \Pr(c_{ikr})), \tag{8}$$

where β_{pih} is the household-specific marginal utility of income for an item in category i, and $\Pr(c_{ikr})$ includes all baskets that contain the specific i, k, r item. Similarly, the marginal effect of a change in the price of an item in a different category (j), of a different brand (l) in the same store on the probability of purchasing an item in category i, when the items are

[7] The practical limitations of describing 2^I choices are somewhat obvious. Recently, others have developed ways to either reduce the dimensionality of the $\mathbf{b}_{ht}$ vector, or of estimating it more efficiently. Kwak, Duvvuri, and Russell (2015) focus on "clusters" of items within conventional category definitions, while Moon and Russel (2008) project the $\mathbf{b}_{ht}$ vector into household-attribute space, so only 2 parameters are estimated. Kamakura and Kwak (2012) use the random-sampling approach of McFadden (1978) to reduce the estimation burden while leaving the size of the problem intact. Because our problem is well-described with only a small number of categories (4), we estimate the MVL model in its native form.

in the same baskets is given by:

$$\frac{\partial \Pr(c_{ikr})}{\partial p_{jlr}} = -\beta_{pih} \Pr(c_{ikr}) \Pr(c_{jlr}), \tag{9}$$

and the marginal effect of change in the price of an item that may be in the same category, and of the same brand, but in a different store is:

$$\frac{\partial \Pr(c_{ikr})}{\partial p_{iks}} = -\beta_{pih} \Pr(c_{ikr}) \Pr(c_{iks}) \tag{10}$$

for all products not in the same store. With these expressions, we can estimate an entire matrix of price responses, for all items with respect to all other items, whether they are from the same brand, category, and store, or if they differ entirely.

In the absence of unobserved heterogeneity, the MVL model is estimated using maximum likelihood in a relatively standard way. However, because we allow a range of parameters to vary across panel observations, the likelihood function no longer has a closed form. Therefore, the model is estimated using simulated maximum likelihood (SML, Train 2003), using $r = 1, 2, 3....R$ simulations. Define a set of indicator variables z_k that assume a value of 1 if basket k is chosen and 0 otherwise, so the likelihood function for a panel over h cross-sections and t shopping occasions per household yields a simulated likelihood function written as (Kwak, Duvvuri, and Russel 2015):

$$\mathcal{L}_h(\mathbf{b}_{ht}) = \frac{1}{R}\sum_{r=1}^{R}\prod_{t}\prod_{k}(\Pr(\mathbf{b}_{ht} = \mathbf{b}_{ht}^{k})^{z_k}, \tag{11}$$

where the joint distribution function for all possible baskets is given in (7). We then take the log of (11), sum over all households, and maximize with respect to all parameters: $LLF(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\theta}) = \sum_{h=1}^{H} \log\ \mathcal{L}_h(\mathbf{b}_{ht})$. To increase the efficiency of the SML routine, the simulated draws follow a Halton sequence with 50 draws.

The MVL is powerful in its ability to estimate both substitute and complimentary relationships in a relatively parsimonious way, but suffers from the curse of dimensionality. That is, with N products, the number of baskets is $N^2 - 1$, so the problem quickly becomes intractable for anything more then a highly stylized description of the typical shopping basket.

Therefore, we restrict our attention to four categories that are likely to exhibit a pattern of both substitute and complementary relationships. Other methods have been developed in order to explicitly address the problem of dimensionality inherent in shopping-basket demand estimation (Kamakura and Kwak 2012), but have not yet proven to be as amenable to estimation in panel-scanner data as the RP-MVL.

To this point, the development of the MVL model is relatively standard. However, in our application we are interested not only in the magnitude of each of the Θ_{ij} parameters (dropping the household subscripts for clarity), but how a consumer's willingness to substitute (or complement) between categories affects equilibrium prices charged by retailers in each category, and how the resulting margins are divided between retailers and manufacturers. We use the parameter estimates from the RP-MVL model above to condition equilibrium pricing behavior by retailers, and their bargaining power relative to manufacturers in the vertical channel using the Nash bargaining model developed in the next section.

3 Bargaining Power Model

In this section, we describe the empirical model used to estimate the effect of complementarity on brand-level bargaining power. For this purpose, we use the vertical Nash-in-Nash model developed by Misra and Mohandy (2006) and Draganska, Klapper, and Villas-Boas (2010). Our model differs from either of these studies, however, in that we explicitly account for the effect of complementarity. Horn and Wolitzky (1988) show that complementarity is likely to be critical in influencing the level of bargaining power possessed by either side because downstream-substitution patterns affect the disagreement profit earned by each party should negotiations fail. Disagreement profit, in turn, depends upon how much the market share of each product would rise if the object of the negotiation is dropped from the product line-up. With strict-substitute demand models, the notion that market share will rise if another product is dropped is a given as it is enforced, mathematically.

With complementary products, however, the effect is not as straightforward. If I am a retailer, and negotiations fail with my pasta-sauce supplier, I will still sell pasta-sauce from another supplier (substitute product). If I also sell pasta from this same pasta-sauce supplier (a complementary product), then the supplier's loss in sales is magnified by the complementary relationship between pasta and sauce, but I continue to sell pasta from another supplier. The disagreement profit for the retailer, therefore, is higher in the complementarity case than it is when products are constrained to be strict substitutes, so retailer bargaining power is expected to be higher. Ultimately, however, the complexity of the relationships involved in any given shopping basket means that the implications of complementarity for bargaining power is an empirical question. In this section, we describe how the Nash-in-Nash bargaining power model applies to the case of shopping-basket shoppers.

We characterize the marketing channel as consisting of several, multi-product retailers, and our several, multiple-product suppliers that sell to each of our sample retailers. We assume retailers arrive at a Nash equilibrium in horizontal competition, pricing as if they were Bertrand-Nash competitors selling differentiated products. Following recent developments in the empirical literature on vertical relationships, we then assume the supplier achieves a Nash bargaining solution (Horn and Wolinsky 1988) with each of the retailers independently, and estimate the resulting bargaining power parameter that divides the total margin (from marginal production cost to retail price) between the supplier and retailers according to their relative negotiating abilities (Draganska, Klapper, and Villas-Boas 2010). We begin by solving for the optimal margin values, and then solve for the Nash bargaining solution.

Beginning with the retailer decision, and suppressing time period index (t) for clarity, retailer g sets a price for each item under a maintained assumption of Nash rivalry to solve the following problem: $\pi^g = \max_{p_j} \sum_{j=1}^{J_g} (p_j - c_j^r - w_j) M s_j, \;\; g = 1, 2, ..., G$, where M is total market demand, w_j is the wholesale price, c_j^r are unit retailing costs, s_j is the market share defined above, and retailer g sells a total of J_g products. Marginal retailing costs are assumed to be constant in volume, and a function of input prices, which is plausible given the share of store-sales accounted for by any individual product. The solution to this problem is written in matrix notation as: $\mathbf{m}^g = \mathbf{p} - \mathbf{c}^r - \mathbf{w} = -(\mathbf{\Omega}^g * \mathbf{s}_p)^{-1}\mathbf{s}$, where $\mathbf{m}^g$ is a vector of retail margins, $\mathbf{p}$ is a $J \times 1$ vector of prices, $\mathbf{w}$ is a $J \times 1$ vector of wholesale prices, $\mathbf{c}^r$ is a $J \times 1$vector of retailing costs (estimated as a linear function of retailing input prices), $\mathbf{s}$ is a $J \times 1$ vector of market shares, $\mathbf{s}_p$ is a $J \times J$ matrix of share-derivatives with respect to all retail prices, Ω^g is a retail ownership matrix, with each element equal to 1 if the row item and column item are sold by the same retailer, and 0 otherwise, and $*$ indicates element-by-element multiplication. Equilibrium retail prices, therefore, are determined by demand interrelationships at the retail level in Bertrand-Nash rivalry.

If retail prices are assumed to be determined by the Bertrand-Nash game played among retailers, and marginal production costs determined by the engineering relationships that govern the cost of making each item, then the allocation of the total margin (from retail prices to marginal production costs) depends on how the wholesale price (w_j) is determined. Wholesale prices, in turn, are assumed to be determined by a Nash bargaining process (Horn and Wolinksy 1988; Draganska, Klapper, and Villas-Boas 2010). In a Nash bargaining solution, the allocation of the total margin between wholesalers and retailers depends on two elements: (1) the disagreement profit that results when negotiations fail and the product is not sold, and (2) the bargaining power parameter, which is a function of the inherent bargaining position of the two players. The disagreement profit term reflects the fact that if a product is not sold, the sales, and profits, of all the other items sold by the retailer, or manufacturer, are affected by the nature of the demand interrelationships each face. Draganska, Klapper, and Villas-Boas (2010) solve for the equilibrium relationship between wholesale and retail prices by maximizing the Generalized Nash product in wholesale prices for product j:

$$GN = (\pi_j^g(w_j) - d_j^g(m_j^g))^{\lambda_j}(\pi_j^f(w_j) - d_j^w(m_j^w))^{(1-\lambda_j)}, \tag{12}$$

where w_j is the wholesale price, $d_j^w(m_j^w)$ is the disagreement profit to the supplier for product j, which depends on the supplier's margin, m_j^w, and $d_j^g(m_j^g)$ is the disagreement profit to the retailer for failing to arrive at an agreement to sell the same product. In this expression,

λ_j is the bargaining power parameter, which allocates the share of profit to the retailer (λ_j) and the wholesaler ($1 - \lambda_j$) from the trade of product j. The first-order condition to maximizing the Generalized Nash product is (dropping the product subscript and arguments of the disagreement profit):

$$\frac{\partial GN}{\partial w} = \lambda(\pi^g - d^g)^{(\lambda-1)} \frac{\partial \pi^g}{\partial w}(\pi^f - d^f)^{(1-\lambda)} + (1-\lambda)(\pi^g - d^g)^{\lambda}(\pi^f - d^f)^{-\lambda} \frac{\partial \pi^f}{\partial w} = 0. \quad (13)$$

This expression simplifies to give the equilibrium relationship between retail and wholesale prices as a function of their respective disagreement profits, and the relative bargaining power parameter:

$$\lambda \left((\pi^f - d^f) \frac{\partial \pi^g}{\partial w} \right) + (1-\lambda) \left((\pi^g - d^g) \frac{\partial \pi^f}{\partial w} \right) = 0. \quad (14)$$

Because retail prices are assumed fixed at the BN solution, the derivatives $\frac{\partial \pi^g}{\partial w} = \frac{\partial \pi^f}{\partial w} = Ms$ so this simplifies to: $(\pi^g - d^g) = \left(\frac{1-\lambda}{\lambda}\right)(\pi^f - d^f)$. Stacking over all item-profits provides a simple solution in matrix notation that defines the equilibrium bargaining power parameter, and the margins for each item:

$$\mathbf{m}^f = \left(\frac{1-\lambda}{\lambda} \right) [\Omega^f * \mathbf{S}]^{-1} [\Omega^g * \mathbf{S}] \mathbf{m}^g, \quad (15)$$

where Ω^f is the $J \times J$ manufacturer ownership matrix (with element $= 1$ if the manufacturer owns product j and zero otherwise), $\mathbf{m}^f$ is the manufacturer margin, and $\mathbf{S}$ is the matrix that defines the incremental profit between when a product is sold, and when it is not (see Draganska, Klapper, and Villas-Boas 2010 for details on its construction). Substituting the expression for retail margins ($\mathbf{m}^g$) above, and solving for the total margin gives:

$$\mathbf{p} - \mathbf{c}^f - \mathbf{c}^r = -\left(\frac{1-\lambda}{\lambda} [\Omega^f * \mathbf{S}]^{-1} [\Omega^g * \mathbf{S}] + \mathbf{I} \right) [\Omega^g * \mathbf{s}_p]^{-1} \mathbf{s}(\mathbf{p}), \quad (16)$$

for the final estimating equation, where $\mathbf{c}^f$ is a vector of manufacturing costs, estimated as a linear function of manufacturing input prices.

In our empirical application, we recognize that bargaining power is likely to vary by each retailer-manufacturer dyad in the data. Therefore, we allow the λ parameter to be randomly distributed over the entire category-retailer-brand sample ($\lambda_j = \lambda_{j0} + \lambda_{j1}\nu_3,\ v_3 \sim N(0, \sigma_3)$) so that bargaining power reflects any factors that may influence the relative strength of each player's position. Importantly, however, allowing λ to vary randomly also means that we are able to recover a value for the bargaining power parameter for every observation in the data set. In this way, we use a supplementary regression to test whether bargaining power is higher or lower for products that are complements for other products. Determining whether an item is a complement or substitute is not straightforward because the notion of complementarity is defined dyad-by-dyad, yet we seek a summary measure for each item in our data set. Therefore, we use the matrix **S** to determine whether each product is a *net complement* or *net substitute* over all other items in the store. That is, if removing the item from the product lineup reduces the demand for all other products, then it must be primarily a complement, and *vice versa*. We then define a variable measuring the extent of the impact of removing each item on the demand for all other items ($COMP_j$) that captures the complementary ($COMP_j < 0$) or substitute ($COMP_j > 0$) status of the item in question.

Given that the bargaining power estimation routine already controls for the identity of the retailer and other factors, we test our core hypothesis using a straightforward regression model in which bargaining power is estimated as a linear function of the complementarity variable, and an interaction term between complementarity and time such that:

$$\hat{\lambda}_j = \phi_0 + \phi_1 COMP_j + \phi_2 COMP_j * t + \mu, \tag{17}$$

where $\hat{\lambda}_j$is the fitted-value from the random-parameter function described above, μ is an iid random variable, $COMP * t$ is the complementarity variable interacted with a time variable, and ϕ_i are parameters to be estimated.

In this model, our maintained hypothesis is supported if $\phi_1 < 0$, as this implies that retailers tend to have more bargaining power for complementary products than they do for substitute products (recall that the $COMP$ variable is negative-valued as it is measured as the effect on other product shares if the product is removed), and manufacturers, of course, have less. Based on the theoretical insight of Horn and Wolinsky (1988), we attribute this outcome to the exercise of market power in allocating the transaction surplus between the buyer and the seller due to the fact that goods are complements. When retailers sell complementary goods, and manufacturers are able to internalize the effects of selling their products through multiple retailers, then manufacturers' bargaining power will be lower for that set of complementary items. Similarly, if $\phi_1 > 0$ then suppliers earn higher margins on complementary products, as the degree of bargaining power shifts to suppliers when products are complements, contrary to the Horn and Wolinsky (1988) model. Further, if $\phi_2 < 0$ then any complementarity-premium earned by retailers erodes over time, and, by definition, suppliers benefit over time.

4 Data and Identification Strategy

In this section, we describe the French soft-drink data and how we identify the parameters of both the demand model, and the bargaining power model. Our data are from a large-scale French consumer panel maintained by Kantar TNS Worldpanel for the year 2013. The panel is designed to be representative of all French households, so contains observations from all regions, urban and rural, and draw households from across all socioeconomic strata. We draw a random sample of 330 households from the panel, who recorded a total of 29,026 transactions in 2013. As a household panel, the Kantar data includes information on the specific item that was purchased, the package attributes, how much was paid, where and when it was purchased, and a large set of household socioeconomic and demographic attributes.

Due to the dimensionality issues associated with the MVL model described above, we focus on four sub-categories within the soft-drink category: colas, fruit juices, iced teas, and combine all other soft drinks into an "other" category. In order to ensure that the MVL model is empirically tractable, we also focus on sales through the top 4 retailers, and 4 brands in each category that represented both a relatively large amount of volume in the category, and a presence in as many retailers as possible.[8] Focusing on as many of the same brands across retailers as possible is desirable for identification as we capture as much cross-sectional variation in margin behavior as possible. Although this $4 \times 4 \times 4$ design may seem more restrictive than is normally the case in other shopping-basket demand models, it is necessary in our case because we need to be able to isolate specific retail-manufacturer pairs from the demand model through the bargaining-power estimation process.

We identify complementary relationships among items in the 4 sub-categories by specifically choosing products that are often combined in typical shopping-basket purchases. Whether from a demand for variety, purchasing for multiple use occasions, buying for multiple consumers within the buying household, umbrella branding by manufacturers, or some other source, we observe a substantial number of multi-purchase occasions that can be described as evidence of, at least, incidental complementarity if not complete price complementarity. In table 1, the sample-shares of each item-combination are shown in the bottom 15 rows. The data in this table shows that purchases of fruit-juice-only are most common (31%), while combinations of juice-and-other (13.4%) and cola-juice-and-other (10.5%) are also common. Importantly, no item combination is null so that each interaction parameter in the MVL model has sufficient choice-variation to be, at least in theory, identified.

[table 1 in here]

Soft drinks represent an ideal opportunity to examine our research question as beverages are frequently consumed within the household, consumers tend to exhibit a demand for variety in their soft drink purchases, and, on the supply side, several manufacturers produce product lines across many of the sub-categories that are the focus of our analysis. For instance, the Coca Cola company not only produces their namesake brand in the cola sub-category, but Minute Maid in the juice sub-category, Nestea in the iced tea sub-category, and Powerade in the Other category. Further, because of the importance of national brands in the soft-drink category, our data include a number of brands that are offered by the same

[8] Note that this strategy means that the 4 brands are not always the same in all retailers in each category.

manufacturer through all 4 retailers. Because of our focus on bargaining power, variation in pricing and margins for the same brand across retailers is necessary in order to identify differences in bargaining power associated with manufacturer-retailer dyads. Moreover, national brands are a critical element of our model as umbrella branding can be a primary source of purchase complementarity (Richards, Yonezawa, and Winter 2015; Erdem and Chang 2012; Erdem and Sun 2008). If complementarity at the end-user level represents an important source of downstream bargaining power, then it should be manifest in purchases by retailers in this category, if any. The data in table 1 also summarize the market share of each retailer, and each of our focus brands. Clearly, Retailer 1 is substantially larger than the other 3 retailers, particularly Retailers 3 and 4. Other than Brand 1 in the cola category, there does not appear to be any dominant brands in either of the 4 sub-categories, but sufficient variation to identify both the demand model, and the disagreement-profit element of the bargaining power model.

In terms of the pricing model, we use input price indices from the French National Institute for Statistics and Economic Studies to estimate the marginal cost function. For each category, we first define an index of "primary input" prices, that is, water and sugar or sugar substitutes for cola, water and fruit for fruit juice, water and tea prices for tea, and an average of all content-input prices for the other category. We also create an index of packaging prices by averaging the price indices for aluminum, plastic, and glass. Next, we include an index of wages in the beverage industry to account for the labor content of items in each category. We also calculated an index of energy prices from gasoline, and electricity, but they were found to be statistically insignificant, in any combination, so were excluded from the final model. In the pricing model, we aggregated the data by category, brand, and retailer across all household purchases. These averages were weighted by the volume of purchase to arrive at an average price across all participating households. From the data presented in table 2, the resulting average prices contain sufficient variation to identify any variation in retail pricing over time, and over brands offered by different retailers. We also impute a promotion variable at the household level by measuring the difference in price for the same brand at the same retailer from one week to the next. Any price difference that is larger than -10%, and remains for 1 week, is defined as a temporary price reduction, or a promotion. Table 2 presents summary statistics for all input prices, item prices, and promotional activity.

[table 2 in here]

In the demand model, prices are likely to be endogenous (Villas-Boas and Winer 1999). That is, at the household level, the error term for each demand equation contains some information that the retailer observes in setting equilibrium prices: advertising, in-store displays, preferred shelf-space, or a number of other factors that we do not observe in our data. Therefore, we estimate the demand model using the control function method (Petrin and Train 2010). Essentially, the control function approach consists of using the residuals from a first-stage instrumental variables regression as additional variables on the right-side of the demand model. Because the residuals from the instrumental variables regression contain information on the part of the endogenous price variable that is not explained by the instruments, they have the effect of removing the correlated part from the demand equation. Because input prices are expected to be correlated with retail prices, and yet independent of demand, our first-stage control function regression uses the set of input price variables as instruments. We also include brand and retailer fixed-effects in order to account for any endogenous effects that are unique to each item. Although these variables should represent effective instruments, whether they are weak in the sense of Staiger and Stock (1997) is evaluated on the basis of the F-test that results from the first-stage instrumental variables regression.[9] In this case, the F-statistic is 65.4, which is much larger than the threshold of 10.0 suggested by Staiger and Stock (1997). Therefore, we conclude that our instruments are not weak.

We can also draw some stylized facts from our demand data. Our interest in studying

[9] Detailed results from the first-stage instrumental variables regression are available from the authors.

the structural effects of complementarity on bargaining power follows from a simple observation: In our soft-drink data, when items from different categories are purchased together, consumers appear to be willing to pay a significant price-premium for either product, relative to their respective category averages (figure 1). That is, if a consumer purchases only a fruit juice, they would be willing to pay more for the same fruit juice if they also purchased at least one item from another category.[10] While there are many factors that may explain this difference, it is suggestive of a pattern that consumers are willing to pay more for items when combined in a shopping basket, than when purchased alone.[11] Whether this represents a greater demand for complementary items remains to be determined by estimating the MVL model described above, and calculating equilibrium prices for complementary items.

[figure 1 in here]

5 Results and Discussion

In this section, we first present the results from estimating several versions of the MVL shopping-basket model, and then the estimates from the Nash bargaining-equilibrium model. All bargaining-power estimates are conditioned on the preferred specification for demand, in order to ensure that our estimates are consistent across all of the models used. Because we are able to use these estimates to derive a vector of bargaining-power estimates across each category-retailer-brand observation, we then present the results from a supplementary regression of bargaining power on the extent of complementarity associated with each item. In this way, we are able to test our primary hypothesis regarding the relationship between complementarity and bargaining power.

[10] The differences are statistically significant at the 5% level for the juice, iced tea, and other categories, and at 15% for the cola category.

[11] We considered the possibility that this observation was due to the fact that single-category purchases are likely to involve greater quantities, and hence lower unit prices. However, consumers in our sample purchased greater quantities only during multi-category shopping trips for 2 of the 4 categories.

5.1 Demand Model Results

Our demand-model estimates are shown in tables 3 and 4 below. Table 3 presents the structural estimates for each baseline-utility model, while table 4 presents the full set of interaction parameters, estimated from the same model. In each case, we compare the estimates from a fixed coefficient version of the MVL model to one that takes unobserved heterogeneity explicitly into account by including random coefficients for both the marginal utility of income, and the category-interaction parameters. A likelihood ratio (LR) test comparing the fixed and random-coefficient versions of the model yields a test-statistic value of 186.2, whereas the critical Chi-square value at 5% and 7 degrees of freedom is 14.07, so we interpret the results from the preferred, random-coefficient version of the model.

[table 3 in here]

Comparing the estimates between the two models also shows the extent of bias from not accounting for unobserved heterogeneity, as the marginal utility of income, for example, is nearly 1/3 as large in the random-coefficient relative to the fixed-coefficient model.[12] Among the other parameters of interest in the demand model, note that inventory has a strong, negative effect on the probability that a shopping basket contains each category, except in the case of fruit juice. Because fruit juice is the least storable of any category included here, this result is intuitive. Further, promotion generally has a strong, positive effect on demand in each category but tea. Although an interaction term between price and promotion could not be identified in our data, it is likely the case that promoting tea caused the demand curve to rotate, or become more elastic, sufficient to cause the net effect on category-demand to become negative. In each case, the control function parameter was statistically significant, which implies that endogeneity is an important feature of our data. Of more interest with this model, however, is the sign and significance of utility-interactions among categories.

Based on the estimates in table 4, we conclude that there are significant interaction ef-

[12] Note that we restrict the marginal utility of income to be equal across all categories as, logically, this parameter is an attribute of household preferences and should not vary across categories.

fects associated with purchasing items from different categories together in the same shopping basket. In fact, because each mean-estimate is positive, these results suggest that complementarity is rather the rule than the exception. Because the scale parameter associated with 4 of the 6 interaction-pairs are negative, however, many of the point-estimates for specific items will indeed be negative in total. This is particularly true for the Cola, Fruit Juice interaction parameter, and the Fruit Juice, Other interaction parameter, which show relatively large scale estimates. In general, the statistical significance of these interaction parameters suggests that models that do not allow for utility-interaction among category purchases are fundamentally mis-specified as complementarity is likely to be important. Our interest in this paper, however, does not lie in identifying complementarity *per se*, but rather its impact on equilibrium pricing, and bargaining power. We examine these effects in the next section.

[table 4 in here]

5.2 Bargaining Power Results

Our empirical bargaining power model is structural in nature in the sense that describes how the total margin (retail price less production and distribution cost) is allocated between the manufacturer and retailer, and the bargaining power parameter is identified by variation in the rate at which changes in cost are passed-through to the retail level. Estimates from the base bargaining power model, and a fixed-coefficient alternative, are shown in table 5. Similar to our approach in evaluating the importance of unobserved heterogeneity for the demand model, we conduct a LR specification test in order to determined the preferred form of the pricing model. Using the results in table 5, the Chi-squared LR statistic is $1,180.2$, while the critical value is 3.84 with on degree of freedom. Consequently, we reject the fixed coefficient version and interpret the bargaining power estimates allowing for random variation of the bargaining power parameter. From a practical perspective, allowing λ to vary over time by retailer also allows us to identify factors that may or may not be associated with variation in market power over time.

[table 5 in here]

The bargaining-power estimates are found after controlling for variation in input prices, and retailer-fixed effects. Interpreted at the mean of the λ point-estimates, we find that retailers earn approximately 2/3 of the total margin across all of our sample beverage categories.[13] This finding is somewhat surprising, given the importance of large, multi-national beverage manufacturers such as Coca Cola and Pepsico, but reflects the fundamental economics of selling through oligopoly retail channels. Although net margins in the retailing industry may be traditionally low, these findings suggest that retailers still earn a relatively large share of the price-cost margin, but much of these rents are absorbed by the fixed costs of retailing.

5.3 Bargaining Power and Complementarity

The point estimate in table 5, however, does not tell us anything about the relationship between bargaining power and complementarity. Ailawadi, et al. (2010), however, argue that explaining variation in bargaining power is an important insight that needs to come out of the vertical relationships literature. Therefore, we present the results from a supplementary regression of bargaining power on a measure of complementarity, and retailer fixed effects, in table 6. Our primary hypothesis concerns the empirical relationship between bargaining power and complementarity. Complementarity means that retailers, who internalize pricing externalities from selling products that are related in demand, earn lower margins on complementary products (Rhodes 2015; Zhou 2014) relative to items that are substitutes in demand. Therefore, retailers' disagreement profit is lower for complementary products. Manufacturers negotiate with retailers' incentives firmly in mind, so complementarity should imply more retailer bargaining power, and lower manufacturer power, relative to the usual substitute-products case.

We investigate this question in table 6, in which we estimate a model that shows how λ to

[13] Note, however, that this does not mean that retailers earn fully 2/3 of the profit as manufacturers earn some of the disagreement profit according to equation (15), depending on the re-allocation of demand.

varies over retailers, and with the degree of complementarity. In this table, Model 1 considers the possibility that retailers' bargaining power erodes over time, while Model 2 removes the time-decay effect. Model 3 includes a binary indicator ($Cat * Mfg$) that captures the effect of manufacturers that sell items in multiple categories. From the estimates reported in this table, we find support for our hypothesis. Namely, because the $COMP$ variable is continuously valued, and negative for a product that complements others, these results suggest that complementary products are associated with a share of the total margin that is approximately 28% greater from the retailers' perspective, *ceteris paribus*. Said differently, if an item is complementary with other items, then that item is associated with a share of the total margin that is almost one-third higher for the retailer compared to a different item that tends to substitute for others. Although we allowed for the possibility that retailer bargaining power also erodes over time, we failed to reject the null hypothesis of no time-dependency over time. Although it is likely that bargaining power does change over a longer time-series, a one-year time period is not sufficient to capture changes in retailer-manufacturer relationships in our data.

[table 6 in here]

The estimates in table 6 also show that Retailers 2 and 3 appear to be slightly more successful in bargaining with the set of manufacturers in our data compared to Retailer 1. While we cannot disclose the identity of the retailers, Retailers 2 and 3 are far larger, measured by sales, relative to Retailer 1, so a high degree of bargaining power is perhaps to be expected. This finding also suggests that there is a substantial component of the variation in bargaining power that is due to differences in size, managerial effectiveness, product-mix, geographical distribution or other factors that affect performance in the vertical channel.

Manufacturers may also offer items across-categories, whether complementary or not. There are two possible effects on their bargaining power: First, if a manufacturer offers a number of "must have" national brands in key categories, then it may be the case that manufacturer barganing power rises if it controls brands in a number of categories. Second, a manufacturer may offer a "full line forcing" or bundling arrangement in order to ensure that the retailer provides its brands as wide of coverage as possible. Ho, Ho, and Mortimer (2012) find that such an arrangement in the video rental industry is responsible for lower wholesale prices, and, often, lower supplier profits. When we estimate a version of the bargaining power model in which we control for both complementarity and a binary indicator for multi-category presence (Model 3), we find empirical support for the findings of Ho, Ho, and Mortimer (2012).[14] That is, a multi-category presence is associated with higher retailer bargaining power, so it appears as though manufacturers in the soft drink industry are willing to give up value in order to secure broad coverage for all their brands.

The analysis in tables 6, however, concerns only the exogenous part of bargaining power, or the λ parameter that divides the share of the total margin into the part earned by the retailer, and the part earned by the manufacturer. How the level of each margin varies with complementarity, however, is also of interest. We offer some evidence in that regard in table 7. In this table, we calculate the implied total, retail, and manufacturer margins, as well as the prices received by the retailer. The findings in this table show that the positive relationship between complementarity and retailer bargaining power appears to be driven largely by two categories – colas and fruit juice – while bargaining power in the other two categories is more equally shared. From the summary statistics in table 1, it is clear that the majority of shopping baskets that contain soft drinks consist of some combination of colas and fruit juices. Therefore, if complementarity is indeed an important influence on the balance of negotiating power between retailers and manufacturers, it is likely to involve these two categories. Further, total margins in the cola and fruit juice categories appear to be substantially smaller for items that have a complementary relationship with others relative to those that have a substitute relationship, even when, in the case of fruit juice, the average retail price is higher. This finding suggests that retailers and manufacturers are willing to take smaller margins on items that drive traffic to other, more profitable categories.

[14] The specific estimates are available from the authors upon request.

Nonetheless, this table shows that bargaining power, and margins, differ considerably among categories.

[table 7 in here]

Our findings are critical to outcomes for vertical relationships in the food industry, but are also relevant to a broad class of retailer-manufacturer relationships. Because food is typically purchased from multi-product retailers, in combinations that include many different pairs of complements and substitutes, the supermarket case represents an ideal context in which to investigate our research question. But, many types of manufacturers sell complementary items into oligopolistic retail channels, whether the context is computer accessories and hardware (Dell, Lenovo), sporting goods and accessories or apparel (Adidas, Specialized), or farm equipment and data services (John Deere, New Holland). In each case, retailers have expanded over time to take advantage of the incentives inherent in multi-product retailing – generally defined as economies of scope and scale – but there has been no research to this point that identifies bargaining power as an additional explanation for the expansion of multi-category retailers. In fact, as retailers begin to sell through multiple channels, including online, bricks-and-mortar, and print-catalogue, the complementarity inherent in cross-channel selling may further manifest in even higher retailer margins through the mechanism we identify.

6 Conclusion and Implications

In this paper, we investigate the role of complementarity in influencing the relative bargaining power between retailers and manufacturers in a vertical channel. Based on theoretical models of bargaining in a vertical channel, with multi-product retailers and manufacturers (Horn and Wolinsky 1988) we expect that the nature of demand relationships in the downstream market are critically important to how bargaining power manifests in the share of the price-cost margin earned by each party. Namely, we expect downstream complementarity to be associated with higher levels of retailer bargaining power as manufacturers' disagreement profit is lower if products are purchased together by consumers in the retail market. Lower disagreement profit means that manufacturers have an incentive to reach agreements to sell complementary products through their retail partners, and retailers negotiate with this understanding in mind.

We test our hypothesis using a new model of shopping-basket demand that accounts for both the discrete nature of category-level purchases, and the complementarity associated with combining items from several categories on each trip to the store. The MVL model is able to capture the observation that some pairs of items from different categories tend to be purchased together, even when they are not complements in the traditional sense of bread-and-better, or ketchup-and-hamburger. We apply the MVL model to a sample household-level data from four soft-drink categories purchased by French households in the 2013 calendar year, focusing on purchases made by households at the top four retail chains, buying the top four brands sold across all retailers.

We find that selling complementary product pairs is associated with roughly 9% greater retailer margin-share than would otherwise be the case. That is, retailers are able to enhance their bargaining power relative to manufacturers by selling complementary products across categories. When entering negotiations, retailers understand that manufacturers have to offer a broad array of items across different categories in order to extend their brand appeal. Knowing the pressures faced by manufacturers, retailers negotiate accordingly, and are able to extract greater rents in the vertical channel by leveraging the fundamental economics of multi-product selling.

Our findings are likely relevant to other markets in which retail complementarity is important. As brands expand across related categories, and even related channels, retailers will be able to take advantage of the fact that manufacturers need to be omni-present in order to stay in the minds of consumers. Whether in the technology, sports, industrial equipment, or other markets, retailers share a common attribute of being the primary means by which manufacturers are able to reach consumers – consumers who prefer to purchase goods from one outlet.

Our research is not without limitations. First, we focus our empirical analysis on a single super-category of items, namely soft drinks. Future research that extends our approach to data from other food categories, or even other categories of non-food products, would be valuable. Second, our analysis is restricted to the particular context of French retailing. For our results to generalize beyond the French context, the nature of bargaining relationships between manufacturers and retailers would have to be at least similar. Third, our findings are also limited to the European case where anti-trust restrictions to not shape retailer-manufacturer bargaining, as the Robinson-Patman Act does, at least nominally, in the U.S. Given the weakness of the Robinson-Patman law, however, it would be of real interest to use the approach described here to examine the effectiveness of the law itself (Luchs et al. 2010).

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Table 1. Summary of Sample Shares

Retailers / Brands			Baskets		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Retailer 1	0.353	0.478	Cola Only	0.088	0.284
Retailer 2	0.278	0.448	Fruit Juice Only	0.310	0.462
Retailer 3	0.190	0.393	Iced Tea Only	0.014	0.119
Retailer 4	0.179	0.384	Other Soft Drink Only	0.082	0.275
Brand 1, Category 1	0.300	0.458	Cola and Juice	0.098	0.297
Brand 2, Category 1	0.031	0.172	Cola and Tea	0.005	0.068
Brand 3, Category 1	0.001	0.030	Cola and Other	0.055	0.229
Brand 4, Category 1	0.022	0.147	Juice and Tea	0.017	0.130
Brand 1, Category 2	0.171	0.377	Juice and Other	0.134	0.340
Brand 2, Category 2	0.071	0.257	Tea and Other	0.008	0.090
Brand 3, Category 2	0.044	0.204	Cola, Juice, and Tea	0.017	0.130
Brand 4, Category 2	0.004	0.063	Cola, Juice, and Other	0.105	0.307
Brand 1, Category 3	0.074	0.261	Cola, Tea, and Other	0.005	0.073
Brand 2, Category 3	0.013	0.115	Juice, Tea, and Other	0.028	0.164
Brand 3, Category 3	0.003	0.055	Cola, Juice, Tea, and Other	0.032	0.177
Brand 4, Category 3	0.065	0.476			
Brand 1, Category 4	0.066	0.248			
Brand 2, Category 4	0.059	0.237			
Brand 3, Category 4	0.046	0.209			
Brand 4, Category 4	0.016	0.125			

Note: Brand and retailer identities cannot be disclosed.

Table 2. Summary of Soft Drink Pricing Data

Variable	Units	Mean	Std. Dev.	Min.	Max.	N
Aluminum Price	Index	93.800	4.989	86.700	102.400	3328
Plastic Price	Index	106.300	0.332	105.700	106.900	3328
Glass Price	Index	104.967	0.661	103.500	105.700	3328
Sugar Price	Index	147.106	7.636	134.100	158.500	3328
Gasoline Price	Index	113.156	2.265	110.300	118.000	3328
Electricity Price	Index	115.331	4.921	107.300	121.300	3328
Sugar Substitute Price	Index	104.588	0.700	103.510	106.010	3328
Fruit Price	Index	2.578	0.115	2.433	2.778	3328
Tea and Coffee Price	Index	114.602	1.001	112.600	116.000	3328
Bottled Water Price	Index	110.010	0.533	108.500	110.800	3328
Beverage Industry Wage	Index	110.650	0.415	110.000	111.100	3328
Cola Price	Euros / liter	0.891	0.245	0.295	1.808	3328
Fruit Juice Price	Euros / liter	1.855	0.538	0.756	3.333	3328
Iced Tea Price	Euros / liter	0.918	0.221	0.226	2.500	3328
Other Soft Drink Price	Euros / liter	1.106	0.405	0.212	9.909	3328
Cola Promotion	%	0.060	0.238	0.000	1.000	3328
Fruit Juice Promotion	%	0.052	0.222	0.000	1.000	3328
Iced Tea Promotion	%	0.064	0.244	0.000	1.000	3328
Other Soft Drink Promotion	%	0.070	0.255	0.000	1.000	3328

Note: Input prices used to form indices in the final estimated model. Promotion indicators calculated using price-reduction threshold of 10%.

Table 4. Interaction Parameters from MVL

	Fixed Coefficient		Random Coefficient	
	Estimate	t-ratio	Estimate	t-ratio
Cola, Fruit Juice	48.4471*	78.4467	59.2950*	96.0119
Scale			-13.8800*	-49.5913
Cola, Tea	97.7647*	251.6550	45.9108*	118.1784
Scale			-8.4682*	-99.9394
Cola, Other	76.0721*	177.6280	42.6219*	99.5219
Scale			-1.0608*	-3.9993
Fruit Juice, Tea	89.2720*	271.4451	73.5761*	223.7192
Scale			21.6681*	5.1517
Fruit Juice, Other	63.3418*	165.5473	77.2406*	201.8725
Scale			-18.9383*	-37.2703
Tea, Other	40.8367*	95.1759	36.4701*	84.9990
Scale			3.2041	1.5656

Note: A single asterisk indicates significance at a 5% level.

Table 3. MVL Demand Estimates

Category	Variable	Fixed Coefficients Estimate	Fixed Coefficients t-ratio	Random Coefficients Estimate	Random Coefficients t-ratio			Fixed Coefficients Estimate	Fixed Coefficients t-ratio	Random Coefficients Estimate	Random Coefficients t-ratio
	Price	-10.3737	-122.4276	-2.9824	-35.1971						
	Std. Dev.			1.4678	1.7505						
Colas	Constant	-6.0480	-21.6088	-3.6304	-12.9709	Tea	Constant	2.2721	5.1544	-4.0582	-9.2063
	Promotion	20.5123	77.3327	11.0433	41.6340		Promotion	-2.5425	-6.1794	-7.6689	-18.6389
	HH Size	-56.1220	-13.3433	0.8892	0.2114		HH Size	-65.1401	-13.4826	146.6066	30.3445
	Income	-0.9482	-1.8660	7.4980	14.7560		Income	1.4321	1.6988	2.3930	2.8387
	Education	-5.7064	-2.7882	-73.9114	-36.1135		Education	-96.3142	-39.4185	-47.4332	-19.4130
	Inventory	-134.3834	-16.0262	-157.1277	-18.7387		Inventory	-165.2920	-17.5644	-212.1655	-22.5453
	Retailer 2	-1.6959	-5.4678	-14.9241	-48.1185		Retailer 2	-1.7250	-4.5174	-23.8198	-62.3808
	Retailer 3	-4.8390	-11.5203	2.6727	6.3631		Retailer 3	0.4224	1.1767	0.9384	2.6144
	Retailer 4	-8.4185	-61.4891	2.2564	16.4810		Retailer 4	-0.0597	-0.3504	7.5996	44.6397
	Brand 1	36.4939	130.7971	28.5176	102.2093		Brand 1	39.9710	53.1157	53.1672	70.6515
	Brand 2	2.3531	8.0344	5.1927	17.7297		Brand 3	4.2490	8.6083	10.1732	20.6103
	Brand 3	-27.6063	-9.3762	-34.8226	-11.8271		Brand 4	-6.6287	-24.8196	-13.7564	-51.5075
	Brand 4	58.0533	177.6811	-2.8304	-8.6630						
	CF	-10.6674	-38.1133	-15.3591	-49.5210		CF	-17.0717	-64.3616	-26.4124	-192.9166
Fruit Juice	Constant	-1.9568	-7.9419	-2.0928	-8.4939	Other	Constant	-4.8275	-17.8587	-3.3627	-12.4400
	Promotion	5.0975	44.2928	15.3943	133.7640		Promotion	15.6611	92.7254	11.9560	70.7881
	HH Size	-164.2370	-45.4800	-102.8920	-28.4925		HH Size	-104.8114	-24.6190	-71.5824	-16.8139
	Income	10.4865	31.8333	13.0656	39.6625		Income	3.7661	11.0882	7.8993	23.2571
	Education	-19.4736	-11.0123	-45.6109	-25.7928		Education	-8.1430	-4.0154	-43.7277	-21.5625
	Inventory	54.4302	4.5909	122.5980	10.3404		Inventory	33.1227	3.2762	-12.7122	-1.2574
	Retailer 2	-1.4999	-5.3536	-14.8281	-52.9280		Retailer 2	-2.4039	-8.2860	-15.8365	-54.5862
	Retailer 3	-5.7978	-17.5062	1.6649	5.0270		Retailer 3	-5.7158	-16.9274	1.8109	5.3630
	Retailer 4	-7.3244	-64.0657	2.4833	21.7211		Retailer 4	-7.3527	-56.1555	2.4551	18.7506
	Brand 2	11.2502	0.2847	34.7106	0.8783		Brand 1	7.1033	15.8607	7.5656	16.8928
	Brand 3	3.0818	21.9648	20.7182	147.6651		Brand 2	184.8058	126.2629	19.4588	13.2946
	Brand 4	45.1965	134.4622	2.5195	7.4958		Brand 3	10.4618	60.6124	6.0893	35.2797
	CF	8.8679	104.6567	0.8377	1.9943		Brand 4	6.5542	16.5531	5.6731	14.3279
							CF	7.0862	1.6848	-0.0690	-0.2474
LLF / AIC		-2324.5900		0.0348			-2231.46		0.0334		

Note: CF is the control function parameter. A single asterisk indicates significance at 5%.

Table 5. Estimates of Bargaining Power Models

	Fixed Parameter		Random Parameter	
	Estimate	t-ratio	Estimate	t-ratio
	Non-Random Parameter Estimates			
Primary Input	0.0070*	53.9231	0.0072*	22.4375
Packaging	0.0091*	2.7447	0.0093*	2.3990
Beverage Wages	0.0103*	3.3497	0.0104*	2.9408
Retailer 1	0.0312	1.5598	0.0326*	6.0222
Retailer 2	0.0118	0.5878	0.0180*	3.5757
Retailer 3	0.1752*	8.7722	0.1616*	32.9165
	Random Parameter Estimates			
λ	0.9929	1.0608	0.6776*	173.6314
	Standard Deviation of Parameters			
σ_λ	N.A.	N.A.	1.0817*	199.9353
	Variance of Regression			
σ			0.3847*	226.2765
LLF	-1728.61		-1138.53	
AIC	1.0431		0.6884	

Note: A single asterisk indicates significance at a 5% level.
Estimated with simulated maximum likelihood.

Fig. 1. Single vs Basket Prices

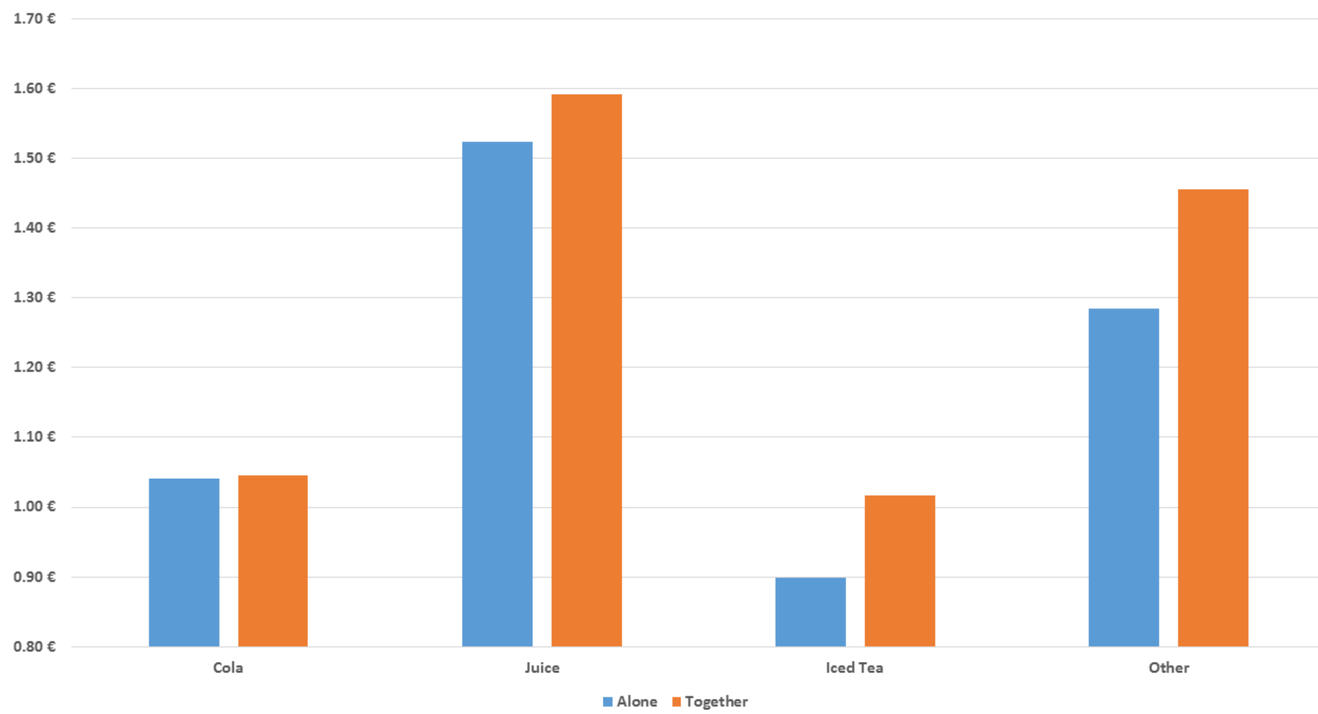

Table 6. Bargaining Power and Complementarity

	Model 1		Model 2		Model 3	
Retailer 1	0.3540*	8.4495	0.3540*	8.4556	0.3169*	7.0454
Retailer 2	0.3848*	9.5946	0.3848*	9.5946	0.3601*	8.6447
Retailer 3	0.3924*	9.6484	0.3924*	9.6484	0.3615*	8.5249
Cat*Mfg					0.0988*	2.2599
Complementarity	-0.2792	-1.8632	-0.2781*	-3.7868	-0.2792*	-3.7932
Comp*Time	0.0042	0.8714				
Random Parameter Scale						
Complementarity	0.0334	1.4477	0.0334	1.4477	0.0331	1.4420
Parameter Variance	1.1630*	73.0509	1.1630	73.0968	1.1620*	72.9466
LLF	-5224.7921		-5224.7910		-5222.0722	
AIC/N	3.2409		3.2409		3.2392	

Note: A single asterisk indicates significance at a 5% level.

Table 7. Margin and Bargaining Power by Complementarity Regime

		Total Margin	Retail Margin	Mfg. Margin	Retail Price	Barg. Power
Colas	Not Comp	0.5401	0.3366	0.2036	0.9933	0.6435
	Comp	0.4567	0.3118	0.1449	0.8451	0.6857
Fruit Juice	Not Comp	0.6620	0.4149	0.2471	1.8494	0.6444
	Comp	0.5517	0.3702	0.1815	1.8980	0.7313
Iced Teas	Not Comp	0.4869	0.3147	0.1722	0.9230	0.6586
	Comp	0.5713	0.3479	0.2233	0.9134	0.6377
Others	Not Comp	0.5615	0.3505	0.2110	1.1656	0.6265
	Comp	0.5613	0.3488	0.2125	1.0866	0.6261

Note: Margins calculated using estimates in table 5.