Inference and Impact of Category Captaincy*

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Abstract

This paper studies *category captaincy*, a vertical relationship whereby the retailer delegates pricing and assortment decisions of an entire category to one of the leading manufacturers within the category. These contracts, which are confidential, can lead to disproportionately higher market shares for the captain's products. The objective of this paper is to infer the existence of such contracts and to quantify their impacts on prices, market shares, and profits of manufacturers and retailers. I use the yogurt category as an empirical setting, in which the captain is either Dannon or Yoplait—the top two brands in the category by national market share. Using Nielsen scanner data, I first estimate a random-coefficient model of consumer demand. I use estimates of the brand-retailer specific shocks and a Bayesian inference model to classify retailers into one of the three categories: Dannon-captained retailers, Yoplait-captained retailers, or non-captained retailers. Conditional on the classified arrangements, I then apply conduct tests to infer that captains eliminate double markups from their own products, while the non-captain products still have double markups. The results from counterfactual experiments show that category captaincy arrangements increase market shares of the captain by about 50%, but they can also increase retailer profits and consumer welfare by eliminating double markups on the captain's products.

Keywords: Vertical Relationships, Category Captain, Bayesian Inference, Conduct Test

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1 Introduction

Many retailers delegate control of category management decisions, such as details about assortment, product placement, shelf design, and pricing of all the brands in the entire category, to one of the category's leading manufacturers, known as a *category captain* (Kurtuluş et al. 2014b, Bandyopadhyay et al. 2009). On one hand, category captaincy offers an efficient way for retailers to outsource category management to a large manufacturer, and streamline the integration of the supply chain. On the other hand, this practice has raised many antitrust concerns. Focusing on the plausible anti-competitive consequences of the practice, a Federal Trade Commission (FTC) report outlined the concerns that a captain could hinder the entry or expansion of other manufacturers, leading to less variety and higher prices for rivals (FTC 2001). However, the confidential nature of the captaincy arrangements has impeded empirical investigations. For example, in a U.S. Senate hearing focusing on the category captaincy practice, only three small business owners out of 79 were willing to testify for fear of retribution from the captain (NPR 2019). There is so little hard evidence available that the American Antitrust Institute called for further empirical evidence and research into the category captaincy practice (AAI 2003).

While the nature of such captaincy arrangements is confidential, the existence of these arrangements can be gleaned from the data evidence that shows significant market share asymmetries between leading brands across different retail chains in some categories. In this paper I focus on the yogurt category in the US, which is dominated by two large competitors, Dannon and Yoplait. Each of them controls around 25% of national market share, and this market share pattern is similar across various geographic markets in the US. However, a significant asymmetry arises when we zoom into the market share distributions of these two leading brands *within* different retail chains. As highlighted in Figure 1, within certain retail chains, Dannon and Yoplait each commands a disproportionately higher market share. Specifically, in about one-fourth of the retailers, Dannon leads the within-chain market share, and sells twice as much yogurt as Yoplait; meanwhile, in another one-third of the retailers this ratio is flipped, with Yoplait selling twice as much yogurt as Dannon. A similar asymmetry is notable in the depth of product assortment as well: the leading brand also sells a greater variety of products within the retailer.

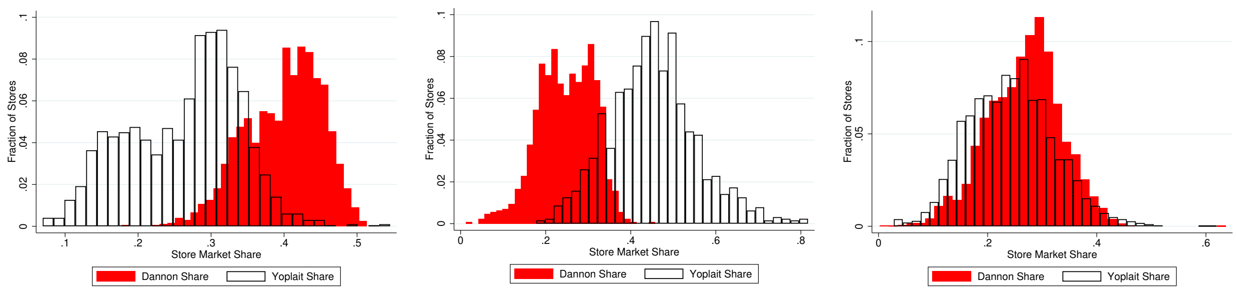
In this paper I propose empirical strategies to infer the presence and prevalence of this confidential vertical arrangement using Nielsen Retail Scanner data. This inference is a necessary step toward achieving the main goal of the paper, which is to evaluate the impacts of category captaincy arrangements on equilibrium prices, market shares, and profits of manufacturers and retailers, as well as consumer welfare.[1]

Figure 1: Store Share Distributions in Three Types of Retail Chains

(a) Dannon Share Greater than Yoplait Share

(b) Yoplait Share Greater than Dannon Share

(c) Dannon and Yoplait Share about Equal



Notes: A leading brand for a given retailer meets the following conditions: (1) The brand leads market share within chain across all markets, (2) the within chain-market share of that brand is greater than the national share for all markets. Panel(a) depicts the store market share of Dannon and Yoplait in retailers with significantly larger Dannon share, Panel(b) depicts the store market share of Dannon and Yoplait in retailers with significantly larger Yoplait share. Panel(c) depicts the store market share of Dannon and Yoplait in retailers where there is no significant asymmetry between the two brands' shares.

In addressing the main research objective, I introduce two inference approaches using the yogurt category as an empirical setting.[2] The first inference test uses a Bayesian classification model based on product assortment and a measure of unobserved quality of product placement within a retailer, such as eye-level display, in-store ads, and shelf space square-footage. I classify retailers into one of the three categories: Dannon-captained retailers, Yoplait-captained retailers, or non-captained retailers. Based on the classification results, the second inference test evaluates a prediction that arises from the theoretical model—specifically, that the captain eliminates double marginalization from its own products, while the non-captain products still have double markups.[3]

To implement the first inference test, one needs to first quantify the unobserved advantage of product placement within a retailer (which I refer to as unobserved quality of

[1]Few papers have access to captaincy arrangements. One example is Viswanathan et al. (2020), which evaluates the economic impact of category captaincy using proprietary information about the arrangements in 24 retailers in frozen food category. My paper on the other hand, develops empirical strategies for the inference and impact of captaincy, given the empirical challenge that these vertical contracts are secretive and unobserved to researchers.

[2]Dannon and Yoplait reportedly engage in category captaincy arrangements with retailers. The following facts and quotes from the industry press suggest that the practice is being used in the yogurt category: General Mills (the parent company of Yoplait) has won Category Captain Awards in the yogurt category for 2011, 2014, and 2018 by Progressive Grocer (Progressive Grocer 2011, 2015, 2018). Danone (the parent company of Dannon) "has built relationships with retailers, constituting a competitive advantage over new entrants or smaller players," according to analysis by the financial services firm, Morningstar, Inc. "It can gain and retain points of distribution by deploying category captains to share local and category-level data with retailers...Such relationships are mutually beneficial, with the vendor becoming an essential retail partner, developing sales strategies to maximise volume and retailers' margins while prioritizing its own brands."(Morning Star Analysis Report 2020).

[3]Double marginalization refers to the distortion caused by the successive markups of independent firms in a distribution channel. The implication that this both reduces firm profits and harms consumers is known as the double-marginalization problem (Gabrielsen et al. 2018).

product placement). To this end, I estimate a demand model in the spirit of Berry et al. (1995) (henceforth BLP) that controls for heterogeneous tastes for observed product characteristics and assortments. I find that the brand-retailer dimension explains 85% of the variance of estimated unobserved quality. Intuitively, how much market share variation can be explained by this brand-retailer component is indicative of how "effective" the unobserved arrangement between retailer and manufacturer can be in shifting the demand. Moreover, the estimated brand-retailer fixed effect is positively correlated with the observed assortment depth, such as number of container sizes or number of yogurt flavors of a brand carried by a retailer. This effect is also persistent over time, consistent with the fact gleaned from industry reports that category captaincy tends to be a long-term agreement. Therefore, I use the estimated $brand \times retailer \times market$ fixed effect as a proxy for the unobserved quality of product placement.

The estimated unobserved quality of product placement exhibits similar asymmetry between Dannon and Yoplait across different groups of retailers identified by market share asymmetry and illustrated in Figure 1. Exploiting the variation in the distributions of the unobserved quality of product placement and observed assortment depth of Dannon and Yoplait across retailers, I classify retailers into types implied by the captaincy arrangement. Consistent with the industry and data evidence, I assume that the sample of retailers is comprised of three types—those who have Dannon as the captain, those who have Yoplait as the captain, and those who manage the category by themselves (referred to as retailer category management, henceforth RCM). I model the joint distribution of unobserved quality of product placement and assortment depth as a finite mixture from these three types of retailers, with a probability associated with each type. I apply Gibbs sampler, a Bayesian inference method, to solve the model. The result suggests that the fraction of retailers potentially using a captaincy arrangement is about 70%. Based on my interviews with industry experts, this fraction is in line with their knowledge of the prevalence of category captaincy.

With the classification of retailers at hand, I proceed to my second inference test focused on pricing. The theoretical prediction from literature implies that the captain eliminates double marginalization from its own products, while the non-captains still have double marginalization (Kurtuluş and Nakkas 2011, Wang et al. 2003). Intuitively, if this captain pricing hypothesis is true, it will translate into price asymmetries (i.e., lower prices of the captain's products, and higher prices of the non captains' products), and heterogeneity in these asymmetric patterns across retailers, varying with captaincy status and identity. This hypothesis has not been tested in empirical settings, however, because the captaincy arrangements are not observed.

My classification of retailers enables me to test the captain pricing hypothesis in the data. From the classification results, I find that the lower price of Dannon (or Yoplait) is correlated with higher estimated probability that Dannon (or Yoplait) is the captain. This data variation helps discriminate between the captain pricing hypothesis and alternative hypotheses such as linear pricing, non-linear pricing (e.g., zero wholesale margin, zero retail margin) commonly considered in the literature (Berto Villas-Boas 2007, Bonnet and Dubois 2010, 2015). I implement the pricing inference test using conduct test methods (Rivers and Vuong 1988) and pricing equations consistent with the captaincy status and captain identity of each retailer. The results show that the captain pricing model provides the most reasonable fit of the data, compared to all the alternative models.

The two sets of inference test results indicate that the category captain introduces asymmetry into unobserved quality of product placement in shelf space and prices across products within a retail chain. This can generate competitive and/or efficiency effects on manufacturers and retailers. I investigate these potential effects of category captaincy in three counterfactual analyses.

The first counterfactual exercise examines the effects of elimination of double marginalization from captain products. I keep the quality of product placement fixed, but change the captain pricing to double marginalization model. Imposing double markups on the captain increases its price by 19.3%, and decreases its share by 53.9%. All of the captain's reduction in market share is picked up by the non-captain brands. In this counterfactual, total profit falls by about 10.1%. The total profit refers to the joint profit of the captain and the retailer. Estimating the split of the total profit between the retailer and the captain is out of the scope of this paper, but in section 6, I provide bounds on the split of the total profit that are consistent with both the retailer and the captain being better off under category captaincy. Consumer welfare also decreases by 7.8%, which is mainly driven by the increase in the average category price.

The second counterfactual experiments with removing the higher quality of product placement that the captain brand receives. I replace the captain's better quality of product placement with the average quality of product placement in RCM retailers. Results show that the captain's market share decreases by about 44.4%. All of this reduction is diverted to the non-captain brands. Total profit decreases by about 11.2%. Meanwhile, consumer welfare increases by 8.4% from the increased quality of product placement of the non-captain products.

The third counterfactual tests whether the captain is distorting the choice sets, and quantifies the impact of any distortions by reconstructing Dannon-captained retailer's choice set to mimic the choice set in RCM retailers in the same market. The captain's market share decreases by about 76.8%. This is caused by two changes: the captain's quality of product placement is reduced, and its number of products decreases by more than a half. However, the change in choice set leads to an increase in consumer welfare by around 10.3%. It also leads to a 16.4% increase in the profit of the alliance between the retailer and the captain.

The results from the three counterfactuals suggest that category captaincy generates an efficiency gain for the alliance between the captain and the retailer from pricing and product placement, but creates significant competitive disadvantages for the non-captain brands. Consumers can benefit from lower average category price from elimination of double markups from the captain brand, but can incur losses from the asymmetry in the quality of product placement and distortions in choice sets. Therefore, the consumer welfare change depends on the relative magnitude of these forces, and varies across different retailers.

The rest of the paper is organized as follows. section 2 provides a review of related literature. section 3 introduces the data and describes some of the key institutional features of category captaincy. I present a stylized supply model in this section to motivate the two inference test approaches. I then present the first inference test in section 4, followed by the second inference test in section 5. section 6 is devoted to the counterfactual analyses of the effects of category captaincy. I conclude the paper and discuss the implications of my findings in section 7. Further computational and data construction details are placed in the Appendix.

2 Literature Review

My paper mainly contributes to two strands of literature: the literature on category captaincy and its impact, and the literature on modeling and inference of vertical relationships.

My stylized supply model is most closely related to Kurtuluş and Nakkas (2011) and T. Gabrielsen (2018). Kurtuluş and Nakkas (2011) analyzes pricing under captaincy. Their analysis reveals that the retailer can use the scarcity of the shelf space to control the intensity of competition between manufacturers to its benefit. But their model does not endogenize the captain competition. T. Gabrielsen (2018) develops a theoretical model where the retailer allows the manufacturers to bid for the right to be the category captain. My model shares the feature of profit sharing with their approach, but also adds to the framework a mechanism on how the profit share is determined in the equilibrium.

More broadly, most of the existing theoretical research on category captaincy can be coarsely grouped into three categories that aim to answer the following questions (Kurtuluş and Toktay 2008): (1) Why will category captaincy arise in equilibrium, under what conditions (Niraj and Narasimhan 2004, Wang et al. 2003); (2) What is the impact of a retailer delegating the pricing or assortment decision to a category captain (Kurtuluş and

Nakkas 2011, Kurtuluş et al. 2014a); (3) What are the antitrust concerns that can arise as a consequence of category captaincy (Subramanian et al. 2010, Kurtuluş et al. 2014b). My paper provides empirical evidence and results that support the theoretical predictions, such as the captain pricing hypothesis, the anti-competitive effect of captaincy, and the potential efficiency gain for the retailer from appointing a captain.

There are only a few empirical papers about category captaincy, due to data limitations. Both Alan et al. (2017) and Kim et al. (2016) rely on data from one retail chain, in two different categories, to study the benefits and drawbacks of category captain. Nijs et al. (2013) use price simulations to evaluate the impact of captain pricing arrangement on retailers, manufacturers, and consumers. Viswanathan et al. (2020) uses confidential information on category captaincy across 24 retailers in a frozen food category. They find that category captaincy has an efficiency effect that leads to savings of carrying an SKU, a market-coverage effect due to the addition of products that a retailer would have otherwise not carried, and a substitution effect leading to addition/deletion of SKUs that favor captains. One key feature distinguishes my paper from their paper. They use data on observed captaincy arrangement reported by the retailer or wholesaler, while my paper introduces a framework for informing captaincy arrangement from limited data. Hristakeva (2019) and Hristakeva (2020) study another form of vertical relationship—vendor allowance. She shows that vendor allowance contracts incentivize the retailers to adjust product assortments.

My paper also contributes to the strand of literature that integrates firm conduct models with vertical relations. (for example, Sudhir (2001), Kadiyali et al. (2000), Berto Villas-Boas (2007), Bonnet and Dubois (2010), Bonnet et al. (2013), Bonnet and Dubois (2015)). These papers consider different vertical contracts between manufacturers and retailers under limited data, and identify the supply-side vertical models. The common approach of this literature is to rely on different contracting models to recover the price-cost margins and other contractual terms for testing between models. I apply a similar conduct test tool for inferring the captain's pricing behavior. But my paper innovates in that I account for heterogeneity in vertical contracts across retailers, that is, different retailers use different captaincy arrangements. Moreover, I allow for asymmetry in pricing and margins across products within a retailer, which is introduced by the captain's price-setting behaviors. This asymmetry in pricing and margins generates important implications on efficiency gain and competition patterns. Both the heteogeneity across retailers and the asymmetry across brands are important factors to take into account given industry knowledge and the empirical evidence.

Besides these two main contributions, my paper also speaks to the early findings in a series of papers by Hwang et al. (2010), Hwang and Thomadsen (2016), Bronnenberg et al. (2007)

that document large and persistent geographic variation in market shares, perceived quality levels, and local dominance in the distribution of national brand shares across markets, and across retailers. Bronnenberg et al. (2009) and Bronnenberg et al. (2012) point to possible explanations such as consumer preference and brand "early entry" advantage. My paper provides another possible mechanism to understand these significant share dispersion, which is the category captaincy arrangement. My findings suggest that the heterogeneity across retailers is equally important, and this heterogeneity is consistent with strong asymmetries in how brands are presented and priced across different retailers, due to the category captaincy arrangements.

3 Category Captaincy

3.1 Industry Background

Ever since its introduction in early 1990s, category captain arrangement has become increasingly common in the sale of consumer goods (Chimhundu et al. 2015). This contracting format is adopted not only by smaller retailers but also by some large and leading retailers such as Walmart, Target, and Safeway (Subramanian et al. 2010, Desrochers et al. 2003). Manufacturers consider the captain position to be a powerful competitive tool: more than eight out of every ten manufacturers stated that they take part in retail category management in order to influence category decisions and stay competitive (Desrochers et al. 2003).

Due to the confidentiality of this practice, not much is known in the literature or trade press about how category captaincy arrangement is made between manufacturers and retailers. Gooner et al. (2011) conducted telephone interviews with 49 retail managers and "reveal that from a value-claiming perspective, retailer–lead supplier category management relationships are informal and do not rely on formal governance agreements and controls." Retailers reportedly charge a fee, auction off, and even demand a cash payment in exchange for the privilege of serving as a category captain (Steiner 2000). Manufacturers who act as category captains often pay the retailers for this privilege, either as a direct payment or indirectly by shouldering the costs of managing the category (FTC 2001). One motivation for a manufacturer to pay is it is purchasing a chance at obtaining monopoly or oligopoly power at the retail level (Carameli Jr 2004). On the other hand, in charging a captaincy fee, retailer seeks to recover a portion of the manufacturer's share of consumer welfare (Gundlach et al. 2019).

I focus on the category captaincy practice in yogurt category. This setting offers several advantages for studying category captaincy: First, as discussed in the introduction, ample industry evidence suggests that the category captain arrangement plays an important role in this category. Second, most yogurt manufacturers take responsibility on delivery, inventory and stocking their products, which allows me to focus on pricing and assortment decisions made by the category captains.[4] Third, the yogurt market in the U.S. is characterized by a proliferation of differentiated products, high fixed costs of carrying a product due to refrigeration, and limited shelf space. As a result, a retailer can only carry a small fraction of all the products, and the decisions on assortment and pricing will have big impacts on competition and welfare. Fourth, the yogurt product attributes can be summarized comprehensively, enabling an accurate characterization of consumer demand. Lastly and perhaps the most importantly, the yogurt market is relatively concentrated. The top two brands—Dannon and Yoplait, each commands about 25% of national market share, and they both actively engage in category captaincy practice.

3.2 Data

Quantity sold, prices and product characteristics of yogurt are obtained from Nielsen Retail Scanner ("RMS") data provided by the Kilts Center at the University of Chicago. RMS data record weekly revenue and quantity sold from over 10,000 participating stores across 198 markets in US. My sample period goes from 2012-2016. Depending on the years, there are around 10,000 stores, 90 retailers in the sample. In Nielsen data I observe brand (e.g. *Dannon*), product line (e.g. *Dannon Light and Fit*) of each UPC (universal product code) sold in the store, as well as product attributes such as size, flavor and organic. A product line typically includes a variety of flavors (e.g. *Dannon Light and Fit, vanilla*), different container sizes and fat content. "RMS" data does not record whether a UPC is on sale, so I infer sales from price time series.[5]

I aggregate the data to parent brand-retailer-market-year level for empirical evidence in subsection 3.3, classification in subsection 4.2, and to product-retailer-market-year level for demand estimation in subsection 4.1 and conduct tests in section 5. In my demand estimation sample, I define a product as a combination of "product line $\times$ size $\times$ fat level", with size grouped into "large," "medium," and "small," and fat level into "low," "medium," and "high." I select the top 25 brands (49 product lines) based on national market share ranking, and all the other brands are subsumed into "other". The sample includes 241

[4]Big manufacturers in yogurt category use a Direct-Store-Delivery (DSD) system to distribute their products to retailers.

[5]Specifically, I infer that a UPC goes on sale if the price of the UPC in that week is lower than average annual price of the UPC in that store by more than half of the standard deviation, and quantity sold of the UPC is higher than average annual quantity sold by more than half of the standard deviation.

products. To translate the sales into market shares, I calculate market size based on retailer-market traffic.[6]

Taking a closer look at the two leading companies Dannon and Yoplait, together they capture on average 50% of yogurt sales during the sample period.[7] Their product portfolios are similar to each other: in 2016, Dannon produces in total 397 UPCs, Yoplait produces 317 UPCs. Both companies each produces eight major product lines, some examples include *Dannon Activia*, *Dannon Danimals*, *Dannon Creamery*, *Yoplait Light Thick & Creamy*, *Yoplait Go-Gurt*. Dannon and Yoplait both manufacture product lines that specialize in Greek-style, kids, natural, whole milk and probiotic yogurt. Despite the asymmetry in market share across retailers, these two brands are sold in all the stores across the nation in the data. Because of perishability of yogurt, both companies operate production facilities across the US to distribute yogurt to surrounding regional markets. For instance, Dannon has plants in Ohio, Utah, Texas, Oregon and New York. Yoplait has plants in Tennessee, Massachusetts, Michigan, California and Minnesota.[8] The two companies have built and developed efficient distribution systems that cover the national markets.

I augment the Retail Scanner data with nutrition information from IRI. The nutrition data collect nutrition information and claims at the UPC level, including information from the Nutrition Facts panel, and health and wellness claims on the packaging, for example, calorie, calorie from fat, fat, trans-fat, saturated fat, sodium, cholesterol, sugar, dietary fiber per serving.

Table 1 reports summary statistics of key variables at the product-retailer-market-year level. Most of the variation in price and product characteristics is attributable to product dimension.

[6] retailer traffic $= \frac{\text{annual retailer revenue}}{\text{annual grocery spending per person}}$

[7] Chobani ranks as the third brand in national market share, controlling about 16.01% of national share. The fourth and fifth brands are Fage (5.56%) and Stonyfield (2.89%). See Table A2 in Appendix A for summary statistics of market shares of the top brands.

[8] Source: https://www.dairyfoods.com

Table 1: Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min.	Max.	Product Variation(%)	Market Variation(%)	Year Variation(%)
Share	0.006	0.009	0	0.16	47.33	8.46	0.143
Outside Share	0.71	0.12	0.24	0.99	-	-	-
Price (per oz)	1.34	0.48	0.42	7.09	67.59	2.34	0.12
Sugar (g/serving)	16.58	6.49	1	58.94	76.84	0.27	0.13
Sodium (mg/serving)	80.32	32.62	0	41	84.3	0.15	0.02
fat (g/serving)	2.45	3.09	0	23	93.57	0.02	0.11
Calorie (per serving)	137.95	42.06	0	320	87.92	0.13	0.02
Organic	0.08	0.28	0	1	90.85	0.11	0.03
Size (oz)	18.15	15.39	1	144	75.43	5.12	.01
Nb of Sales	67.54	115.31	0	1648	51.65	10.22	0.94
Nb of Flavors	4.13	4.90	1	54	75.37	3.28	0.45
N					154,774		

Notes: This table reports summary statistics of key variables for demand estimation, summarized at the product-retailer-market-year level. nb sale is number of UPC-weeks of a product that is on sale over the year within the retailer. One serving is eight ounces.

Table 2 summarizes information about the retailers and markets in the sample. There are in total 113 unique retailers over the 2012-2016 sample periods. 23.4% of them operate in a single market (I classify them as local chains), 58.1% of them operate in multiple markets within the same census region (regional chains), and 18.5% of them span across census regions (national chains). On average I observe 3.66 retailers in a market, and each retailer appears in 7.89 markets.

Table 2: Retailer and Market Summary Statistics

Retailer Level Summary	mean	std	p50	min	max
Number of Stores	117.32	214.01	47	1	1338
Number of Markets	7.89	13.64	3	1	93
Number of Regions	1.28	0.67	1	1	4
Retailer Revenue (in Milion Dollars)	2186.83	4619.25	560.69	0.40	33880.87
Market Level (DMA) Summary	mean	std	p50	min	max
Number of Retailers	3.66	2.38	3	1	15

Notes: This table provides summary statistics for the retailers and markets in the sample. Nielsen define a market using DMAs, which are often tied to major cities, in some places cover more than one city.

In the demand model, I use consumer demographic information to model taste differences across retailers and markets. Consumer demographic data is collected from the Public Use Microdata Sample (PUMS). I select a subset of demographic variables—income, female education and number of kids—that are most correlated with yogurt purchases.[9] In the estimation, I take 1000 random draws per retailer-market-year.[10]

To address price endogeneity in demand estimation, I construct instruments from input costs. Table A1 in Appendix A summarizes the cost data from various sources. I approximate transportation cost by multiplying distance between the market and the closest factory of a product, with diesel price from Energy Information Administration.

3.3 Empirical Evidence

One of the biggest challenges of the study of category captaincy is that researchers typically do not have access to proprietary information on category captain arrangement. From the data we only observe downstream prices and quantities, which are market equilibrium outcomes of demand and supply conditions. Starting from these observable variables in the data, the first step of my analysis is to examine whether the variations in market share and choice set across different retailers are consistent with the existence of category captaincy.

In this section, I present empirical evidence consistent with the presence of category captaincy arrangements. I first document a remarkable asymmetry in market share and assortment distributions between the two biggest brands (Dannon and Yoplait) across different retailers. Then I present a series of stylized facts that suggest that category captaincy arrangement is one of the main reasons that drives the market share asymmetries. It is important to note that the model-free evidence presented in this section is only suggestive of the existence of captaincy arrangement, and is not meant to imply any causality or inference.

The notations used in the this section are: i and j denote either UPC or product line, depending on the level of analysis (for example $i =$ Dannon Light n Fit), b denotes brand (such as Dannon, Yoplait), s store, r retailer, m market, h household, t year.

Market Share Asymmetry. According to the industry evidence, the category captain is usually the largest supplier within chain. Therefore, I start by identifying the market share leader for each retailer. Specifically, I calculate the market share of each brand for each retailer-market-year, and identify a brand as a "leading brand" for a retailer if that brand has the largest within retailer-market share across all markets that the retailer operates in, and the within retailer-market shares are all higher than that brand's national market share.

[9] I use Nielsen Consumer Panel Data ("HMS") to select this subset of demographic variables. "HMS" records actual purchases of each registered household in each store, including price, quantity, product purchased, as well as household demographics. I run logit regression of product characteristics on demographic characteristics to determine which demographics most strongly predict yogurt purchasing behavior.

[10] The sampling weights are predicted from logit regressions of whether the household purchases yogurt on household demographic characteristics.

More than half of the retailers in the sample can be classified as having a market share leader across all the markets in which it operates (55 retailers out of 88, as shown in Table 3). More interestingly, I observe a striking market share asymmetry between Dannon and Yoplait: among the total 88 retailers in the data, around 37.5% of retailers have Yoplait as their market share leading brand, whereas about 22% retailers have Dannon as a market share leader. Without any causal inference about category captaincy arrangement, I label the former retailers as "Yoplait-led" retailers, and the latter ones as "Dannon-led" retailers. While the national market shares between the two brands are almost equal, Yoplait commands almost two times market shares in "Yoplait-led" retailers than Dannon, and the ratio is flipped in "Dannon-led" retailers.

Table 3: Leading Brand, their Market Shares and Percentage of Retailers

Leading Brand	Yoplait-Led	Dannon-Led	Other-Led	Non-Led	National Share
Number of Retailers	33/88	19/88	3/88	33/88	
Percentage of Retailers	37.5%	21.59%	3.41%	37.5%	
Share Dannon	0.250 (0.060)	0.401 (0.045)	0.093 (0.028)	0.269 (0.065)	0.25
Share Yoplait	0.470 (0.088)	0.255 (0.069)	0.127 (0.033)	0.270 (0.082)	0.24

Notes: A leading brand for a given retailer satisfies: (1) the brand leads market share within chain across all markets; (2) within chain-market share > national share for all markets. Other-Led means that the leading brand is a brand other than Dannon or Yoplait (Chobani leads market share in one retailer, Tillamook leads market share in two retailers). Non-Led means that either one of (or both of) the criteria is not met (24 out of 33 Non-led retailers still have Dannon or Yoplait as market share leader in at least one of the markets in which they operate, but the leading brand is not consistent across markets). The table is constructed using data from 2016. Summary statistics from the other years are similar. Standard deviations are in the parenthesis.

From Figure 1, where Panel (a) depicts store shares of Dannon and Yoplait in Dannon-led retailers, Panel (b) depicts store shares of Dannon and Yoplait in Yoplait-led retailers, it is notable that this asymmetry in market share is prominent across all the stores within the two groups of retailers as well, whereas stores in non-led retailers do not show any share asymmetry between Dannon and Yoplait . Similar patterns remain when I zoom into retailers that span across multiple markets (Figure B1 in Appendix B.2).

Market Share Variance Decomposition. To identify and quantify the main source that contributes to this big heterogeneity in market share across brands, markets and retailers, I employ a variance decomposition method developed in Abowd et al. (1999) (hereafter AKM), which projects market share onto retailer, market, retailer-brand and market-brand dimensions:

$$s_{brm} = \gamma_r + \psi_{m(r)} + \gamma_{br} + \gamma_{bm} + \varepsilon_{brm} \tag{1}$$

where s_{brm} is quantity share of Dannon or Yoplait at parent brand-retailer-market level. γ_r is retailer fixed effect, $\psi_{m(r)}$ is market fixed effect; γ_{br} is brand $\times$ retailer fixed effect, γ_{bm} is brand $\times$ market fixed effect.

This regression controls for market-specific factors that can potentially drive the market share variation of Dannon and Yoplait, such as regional distribution or popularity. I decompose the total variance of quantity share into the estimated fixed effect components after estimating the equation, and calculate the percentage of the variance of each component relative to the total variance. Table 4 reports the results (Panel A for share decomposition results, and Panel B for price decomposition results). The Brand $\times$ Retailer dimension (γ_{br}) accounts for the biggest percentage of overall quantity share variance of the two brands, suggesting that the dispersion *across brand-retailer* is the biggest contributor to the overall variation in market share of these two brands, conditioning on market level differences captured by Brand $\times$ Market fixed effects. The results for price decomposition show similar patterns. (Table B4 in Appendix B.3 shows AKM decomposition results for the entire sample, and the conclusions are the same).

Table 4: Market Share Variance Decomposition
Yoplait and Dannon

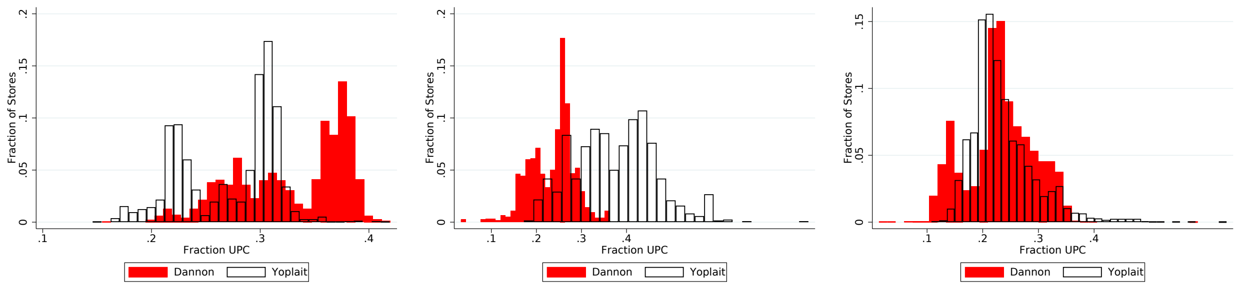
	Panel A		Panel B	
	Share Decomposition		**Price Decomposition**	
	Level	Percentage	Level	Percentage
Total Variance	0.0102	100	0.008	100
Brand $\times$ Retailer	0.005	53.72	0.0035	42.4
Brand $\times$ Market	0.003	33.02	0.0027	32.35
Retailer	0.000	0	0.000	0
Market	0.0006	6.84	0.0005	6.83
R^2	0.889		0.608	
RMSE	0.041		0.073	

Notes: This table shows the results from AKM decomposition on market share and price of Dannon and Yoplait at retailer-market level, using sample from 2016. Price is the price of yogurt of 6oz. Prices and shares are demeaned with brand average before estimation to increase model fit.

Assortment and Price Asymmetry. Besides market share, product assortment of Dannon and Yoplait exhibits asymmetry across the three groups retailers as well. Figure 2 plots the distributions of fraction of UPCs for Dannon and Yoplait across the three groups of retailers identified by the share asymmetry. Fraction of UPCs is calculated as number of UPCs of a brand in a store divided by the total number of yogurt UPCs at the store. Dannon-led retailers sell disproportionately more Dannon UPCs than Yoplait UPCs, and vice versa for Yoplait-led retailers, whereas the non-led retailers do not show any asymmetry. Appendix B.1 presents a linear probability model and shows the same pattern as displayed in Figure 2.

Figure 2: Fraction of UPCs across Stores with Share Asymmetry

(a) Dannon-led Retailers (b) Yoplait-led Retailers (c) Non-Led Retailers



Notes: Dannon-led and Yoplait-Led retailers are classified based on market share asymmetry as described in Table 3. A leading brand for a given retailer satisfies: (1) the brand leads market share within chain across all markets; (2) within chain-market share > national share for all markets.
Panel(a) depicts fraction of UPCs (nb UPC of a brand in store/nb UPC of the store) for Dannon and Yoplait in Dannon-led retailers, Panel(b) depicts fraction of UPCs of Dannon and Yoplait in Yoplait-led retailers. The sample is aggregated to brand-retailer-market level.

Prices of Dannon and Yoplait are also asymmetric across the three different groups of retailers. On average Dannon's price is higher than Yoplait's. But the price difference between Dannon and Yoplait in Yoplait-led retailers is twice as big as the price difference in Dannon-led retailers. (see Table B1 in Appendix B.1).

To systematically examine the correlation between share asymmetry and price or assortment difference of Dannon and Yoplait, I estimate Equation 2, where the dependent variable is an indicator for stores belonging to Dannon-led retailers, and the independent variables (X_{srmt}) include difference in store assortments or price between Dannon and Yoplait (e.g. share of Dannon minus share of Yoplait). γ_t and γ_m are year and market fixed effect respectively.

$$1\{ \text{ store} \in \text{Dannon-led retailer}\} = \beta X_{srmt} + \gamma_t + \gamma_m + \epsilon_{srmt} \tag{2}$$

Table 5 reports estimation results from Equation 2. Each column is a separate regression with an assortment or price difference variable. The results show that stores with larger market share of Dannon also tend to carry more number of flavors of Dannon, put Dannon products more frequently on sale, and set lower prices for Dannon products than for Yoplait products.

Table 5: Correlation between Share Asymmetry and other Marketing Variable Asymmetry

	Dependent Variable: Dannon leads market share				
Diff (Dannon - Yoplait)					
Share	0.682***				
	(0.0242)				
Residual Price		-0.966***			
		(0.0470)			
Price (6oz)			-1.498***		
			(0.0530)		
Nb Flavors				0.0124***	
				(0.000297)	
Sale					0.0427***
					(0.00876)
Constant	0.648***	0.601***	1.039***	0.943***	0.648***
	(0.00267)	(0.00323)	(0.0142)	(0.00776)	(0.00389)
Observations	3,454	3,454	3,406	3,454	3,454
R-squared	0.900	0.890	0.898	0.918	0.877

Notes: The sample is at the store-parent brand level. It includes Dannon and Yoplait brands and Dannon-led and Yoplait-led retailers. Residual price is residualized price from a hedonic price regression. p_6oz is price of yogurt of 6 ounce. DN stands for Dannon, YP stands for Yoplait. Standard errors in parentheses.

Reduced Variety. An anti-competitive concern about captain's opportunistic behavior is that it may exclude smaller brands, leading to reduced overall variety.[11] I compare the number of UPCs, flavors and sizes of small brands (ranking below 50th in national market share) between retailers with a leading brand and retailers without a leading brand, conditional on store size:

$$y_{bst} = \alpha_0 + \beta_2 \mathbb{1}\{\text{store} \in \text{retailer with leading brand}\} + \alpha_2 N_{st} + \varepsilon_{bst} \tag{3}$$

where y_{bst} are number of UPCs, sizes, or flavors of brands that are ranked below 50th in national share ranking in store s. N_{st} is total number of UPCs at store s (summing across all the categories), which approximates the store size. The results shown in Table 6 suggests that retailers with a leading brand tend to have less UPCs and variations of small brands.

[11] Clemmy's, a small ice-cream manufacturer, filed a law suit against Nestlé in 2015. Its CEO claimed that category captaincy decreases the diversity of nutritional options available to consumers, causing public health to suffer as well (Food Navigator 2014). Conversation with industry expert indicates that everything else equal, a captain's new product stands a higher chance to get on the store shelf.

Table 6: Evidence of Reduced Variety in Retailers with Share Asymmetry

VARIABLES	Nb UPCs	Nb Flavors	Nb Sizes
$\mathbb{1}\{s \in \text{retailer with leading brand}\}$	-0.387***	-0.250***	-0.0834***
	(0.0594)	(0.0540)	(0.00541)
Store Size (N_{st})	1.126***	0.926***	0.0120**
	(0.0629)	(0.0571)	(0.00573)
Constant	-2.342***	-1.443***	0.989***
	(0.365)	(0.332)	(0.0333)
Observations	35,897	35,897	35,897
R-squared	0.091	0.089	0.073
mkt FE	yes	yes	yes
mean nb UPC per brand	4.09		
mean nb flavor per brand		3.86	
mean nb size per brand			1.08

Notes: This table shows regression results from Equation 3. Each column is a regression with a different dependent variable. *** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.

To sum up, the model-free evidence presented in this section indicates significant asymmetry in market share and product assortment between the top two brands across retailers, which is consistent with the existence and implication of category captaincy arrangement. In Appendix B, I present more data evidence and two case studies regarding the share, price and assortment asymmetry between the brands across retailers and potential exclusion. There are two important points that are worth emphasizing here: first, I do not observe product placement that the captain can control (e.g. shelf allocation, display, and in-store ads) from the data, but I use a model in section 4 to derive a proxy for it. Second, the data evidence does not imply causality. To formally infer the existence of category captaincy, measure its prevalence and quantify its effects, I rely on model predictions, which I will turn to in the next section.

3.4 Stylized Captaincy Model

In this subsection I present a stylized captaincy model that serves two purposes: (1) to describe the category captaincy practice and its consequences. (2) to rationalize the data patterns, and provide testable implications which will be taken to the data.

Setup. I assume two symmetric brands, each has one product, both sell through one retailer. Each brand has a linear demand: $q_1 = 1 - p_1 + \theta p_2$; $\quad q_2 = 1 - p_2 + \theta p_1$ where θ is the substitution parameter, p and q are price and quantity. Marginal production cost for both brands is c. Throughout the discussion below, I use superscripts to refer to different vertical arrangement scenarios (CC stands for category captaincy, and RCM stands for retailer category management), and subscripts to denote brands. Without loss of generality, I assume that brand 1 is the captain.

The setup is a static, complete information game. In the first stage, the retailer announces a competition for the captain position, and the two brands compete for this position by bidding on ϕ, a fraction of net category profit that the brand keeps for itself. Thus the brand promises a transfer of $(1-\phi)$ of the net category profit to the retailer. The retailer chooses the best option, among Dannon as the captain (DN-CC), Yoplait as the captain (YP-CC), and RCM.[12] Once the retailer makes this decision, the game enters into the second stage—pricing stage, which involves two possible scenarios. If a captain is assigned, the captain chooses retail prices for both brands.[13] In this price-setting process, the captain eliminates double marginalization from its own product by setting wholesale margin to be zero, but it still imposes double-marginalization on the other brand. The non-captain brand chooses its wholesale price anticipating the captain's pricing decision. If no captain is chosen (RCM), then the retailer sets retail prices for both brands, and imposes double markups on both brands. I denote wholesale price as w, profit as Π, and variable category management cost as γ. I assume that the captain's management cost (γ^{cc}) is lower than the retailer's (γ^{rcm}) to reflect the industry perception that captain brand is more efficient in managing the shelves than the retailer.

Solution. The model is solved by backward induction. In the second stage, two potential scenarios are considered: Category Captain scenario and RCM scenario.

(1) Category Captain (CC) Scenario:

The captain chooses both prices to maximize its own profit, which is equal to a fraction (ϕ) of the net category profit (total category profit minus the shelf management cost).

$$\begin{aligned} \max_{p_1,p_2} \quad & \phi\big[\,(p_1-c)\,q_1(p_1,p_2) + (p_2-w_2)\,q_2(p_1,p_2) - \gamma^{cc}\left(q_1(p_1,p_2)+q_2(p_1,p_2)\right)\big] \\ \text{s.t.} \quad & q_1(p_1,p_2)\geq 0, \quad q_2(p_1,p_2)\geq 0 \end{aligned} \tag{4}$$

[12] Throughout this paper, DN stands for Dannon, YP stands for Yoplait.

[13] In this simple model, the choice variable is price—the captain uses pricing strategies to steer demand away from its rivals. In practice, there are potentially other strategic variables (e.g. product choice, product placement), but they will produce the same implications for inferences.

The non-captain brand chooses wholesale price w_2 to maximize its own profit:

$$\max_{w_2} (w_2 - c)\, q_2\,(p_1(w_2), p_2(w_2))$$

Solving this profit maximization problem gives equilibrium quantities and prices $(p_1^{cc}, p_2^{cc}, w_2^{cc}, q_1^{cc}, q_2^{cc})$ (see Table 7). Thus, the equilibrium net category profit under the captaincy scenario is:[14]

$$\Pi_A^{cc} = (p_1^{cc} - c)\, q_1^{cc} + (p_2^{cc} - w_2^{cc})\, q_2^{cc} - \gamma^{cc}(q_1^{cc} + q_2^{cc})$$

And the equilibrium profit of the non captain (brand 2) is:

$$\Pi_2^{cc=1} = (w_2^{cc} - c) q_2^{cc}$$

(2) RCM Scenario: the retailer chooses p_1, p_2 to maximize category profit, incurring shelf management cost (γ^{rcm} $\times$ the category quantity).

$$\begin{aligned} \max_{p_1,p_2} \quad & (p_1 - w_1)\, q_1\,(p_1, p_2) + (p_2 - w_2)\, q_2\,(p_1, p_2) - \gamma^{rcm}(q_1(p_1, p_2) + q_2(p_1, p_2)) \\ \text{s.t.} \quad & q_1(p_1, p_2) \geq 0, \quad q_2(p_1, p_2) \geq 0 \end{aligned} \tag{5}$$

The manufacturer chooses its wholesale price to maximize its profit ($i = 1, 2$):

$$\max_{w_i} (w_i - c)\, q_i\,(w_i, w_j)$$

Solving this profit maximization problem gives $(p^{rcm}, w^{rcm}, q^{rcm})$ which are symmetric for the two brands (Table 7). The equilibrium net category profit under RCM is:

$$\Pi_r^{rcm} = (p_1^{rcm} - w_1^{rcm})\, q_1^{rcm} + (p_2^{rcm} - w_2^{rcm})\, q_2^{rcm} - \gamma^{rcm}(q_1^{rcm} + q_2^{rcm})$$

In the first stage, the two brands bid for captaincy position, and the conditions for equilibrium ϕ^{cc} are:

(1) Outbidding condition (Inequalities (6)): the profit that the captain promises to the retailer ($(1 - \phi^{cc})\Pi_A^{cc}$) should be no less than the profit retailer makes under RCM (Π_r^{rcm}), and no less than the profit that the other brand promises to the retailer ($(1 - \phi_2)\Pi_A^{cc=2}$).

(2) Indifference condition (Inequalities (7)): the profit that the captain makes under captaincy ($\phi^{cc}\,(\Pi_A^{cc=1})$) should be no less than the profit it makes when the other brand is

[14] Π_A^{cc} is the total net profit to be split between the captain and the retailer. The subscript A stands for alliance between the captain and the retailer.

the captain ($\Pi_1^{cc=2}$) or when the retailer manages shelves by itself (Π_1^{rcm}).

$$\text{Outbidding:} \begin{cases} (1-\phi^{cc})\Pi_A^{cc=1} \geq \Pi_r^{rcm} \\ (1-\phi^{cc})\Pi_A^{cc=1} \geq (1-\phi_2)\Pi_A^{cc=2} \end{cases} \tag{6}$$

$$\text{Indifference:} \begin{cases} \phi^{cc}\Pi_A^{cc=1} \geq \Pi_1^{rcm} \\ \phi^{cc}\Pi_A^{cc=1} \geq \Pi_1^{cc=2} \end{cases} \tag{7}$$

Since the game is symmetric, $\Pi_A^{cc=1} = \Pi_A^{cc=2}$, $\Pi_1^{cc=2} = \Pi_2^{cc=1}$. Inequalities (6) put an upper bound on ϕ^{cc} and inequalities (7) put a lower bound on ϕ^{cc}:

$$\hat{\phi}^{cc} \leq 1 - \frac{\Pi_r^{rcm}}{\Pi_A^{cc=1}}$$

$$\hat{\phi}^{cc} \geq \min\left(\frac{\Pi_1^{cc=2}}{\Pi_A^{cc=1}} \quad , \quad \frac{\Pi_1^{rcm}}{\Pi_A^{cc=1}}\right)$$

The two brands undercut each other à la Bertrand. Therefore, the equilibrium bid ϕ^{cc} consistent with brand 1 becoming a captain is:

$$\hat{\phi}^{cc} = \min\left(\frac{\Pi_1^{cc=2}}{\Pi_A^{cc=1}} \quad , \quad \frac{\Pi_1^{rcm}}{\Pi_A^{cc=1}}\right) \qquad \& \qquad \hat{\phi}^{cc} \leq 1 - \frac{\Pi_r^{rcm}}{\Pi_A^{cc=1}} \tag{8}$$

Table 7: Solutions of the Stylized Captaincy Model

Quantities, Prices	CC Scenario	RCM Scenario
	$p_1^{cc} = \frac{c}{2} + \frac{\gamma^{cc}}{2} - \frac{1}{2(\theta-1)}$	$p^{rcm} = \frac{w^{rcm}}{2} + \frac{\gamma^{rcm}}{2} - \frac{1}{2(\theta-1)}$
	$p_2^{cc} = \frac{1+(\theta+1)(\gamma^{cc}+c)}{4} - \frac{1}{2(\theta-1)}$	$w^{rcm} = \frac{(\theta-1)\gamma^{rcm}+c+1}{2-\theta}$
	$w_2 = \frac{1}{2} + \frac{\theta-1}{2}\gamma^{cc} + \frac{\theta+1}{2}c$	$q^{rcm} = \frac{1}{2}[(\theta-1)w + (\theta-1)\gamma^{rcm} + 1]$
	$q_1^{cc} = \left(\frac{\theta}{4} + \frac{1}{2}\right)[(\theta-1)c + (\theta-1)\gamma^{cc} + 1]$	
	$q_2^{cc} = \frac{1}{4}\underbrace{[(\theta-1)c + (\theta-1)\gamma^{cc} + 1]}_{=\text{A}}$	
Profits	$\Pi_A^{cc} = A\left[(\frac{\theta}{4} + \frac{1}{2})(\frac{\gamma^{cc}}{2} - \frac{c}{2} - \frac{1}{2(\theta-1)}) + \frac{1}{4}(\frac{\gamma^{cc}}{2} - \frac{w_2}{2} - \frac{1}{2(\theta-1)}) - \gamma^{cc}(\frac{\theta}{4} + \frac{3}{4})\right]$	
	$\Pi_2^{cc=1} = \frac{1}{8}[(\theta-1)c + (\theta-1)\gamma^{cc} + 1]^2$	
	$\Pi_r^{rcm} = -\frac{1}{2}(w^{rcm} + \gamma^{rcm} + \frac{1}{\theta-1})\left((\theta-1)w + (\theta-1)\gamma^{rcm} + 1\right)$	
	$\Pi_1^{rcm} = \Pi_2^{rcm} = \frac{1}{2}[(\theta-1)w^{rcm} + (\theta-1)\gamma^{rcm} + 1]\left(\frac{(\theta-1)c+(\theta-1)\gamma^{rcm}+1}{2-\theta}\right)$	
1st stage	$\hat{\phi}^{cc} = \min\left(\frac{\Pi_1^{cc=2}}{\Pi_A^{cc=1}}, \frac{\Pi_1^{rcm}}{\Pi_A^{cc=1}}\right) \quad \& \quad \hat{\phi}^{cc} \leq 1 - \frac{\Pi_r^{rcm}}{\Pi_A^{cc=1}}$	

Notes: This table summarizes the equilibrium price, quantity and bid from the stylized captaincy model.

Implications. This stylized model incorporates several key institutional features of category captaincy. Specifically, competition between brands (driven by substitution patterns within chain) for category captain position affects the value of the retailer's outside options, which in turn puts a constraint on category captain's performance. The retailer can take advantage of the upstream competition and extract rents from the manufacturers. Moreover, the revenue sharing mechanism forces the category captain to weigh its own profit against the category profit, which prevents it from completely excluding its rivals.

The model also provides two testable implications which will be taken to the data (See Appendix C for proofs for these predictions and more detailed discussions):

(1) Market share asymmetry: the equilibrium market share of the captain is larger than that of the non-captain; and the market share asymmetry is proportional to the strength of

substitution effect between these two brands: $\frac{q_1^{cc}}{q_2^{cc}} = 2 + \theta$.[15]

(2) Pricing asymmetry: the captain eliminates double marginalization from its own products, while imposing double marginalization on its rivals' products, when it makes retail pricing decisions.

The first prediction suggests an empirical strategy that is based on testing for asymmetry in unobserved quality of product placement that raises demand of a brand, such as eye-level placement, end-of-aisle display, in-store ads: section 4 discusses the implementation of this test. The second prediction informs an empirical approach to test for asymmetry in pricing and margins across products, which will be conducted in section 5.

4 Inference Test One—Quality of Product Placement

The first inference approach tests for asymmetry in unobserved quality of product placement between Dannon and Yoplait across retailers. In this section, I first separate and quantify the unobserved quality of product placement, then I employ a Bayesian inference model to classify retailers into different captaincy models, making use of asymmetry in the estimated quality of product placement.

4.1 Quantify Unobserved Quality of Product Placement

To quantify unobserved quality of product placement from a retailer to a brand, I need to first account for observed demand heterogeneity across retailers and markets. The intuition is that: given a well-identified demand model that controls for price endogeneity, heterogeneous demand factors, and demographic variations, part of what is left in unexplained market share variation can be attributable to the unobserved quality of product placement introduced by the captaincy arrangements.

Demand Model. Consumer choice is modeled using a random utility framework. The indirect utility of a consumer h from consuming a certain yogurt product j at retailer r in market m and year t depends on product characteristics (x_{jrt}), price (p_{jrt}), unobserved product specific component (ξ_{jrt}), and household demographics: [16]

$$u_{jrht} = \bar{u}\left(x_{jrt}, p_{jrt}, \sigma_h\right) + \xi_{jrt} + \varepsilon_{jrht} \tag{9}$$

[15] This prediction is consistent with "competitive exclusion effect" in the theoretical literature.

[16] Market subscript is omitted for ease of presentation.

where ε_{jrht} follows a type I extreme value distribution. Mean utility from the outside option, which is the choice not to purchase yogurt from any of the observed retailers in the data, is normalized to 0.

Utility $\bar{u}\left(x_{jrt}, p_{jrt}, \sigma_h\right)$ is a function of nutrients, container size, number of flavors, price, organic, number of sales and an outside option (const):

$$\begin{aligned}\bar{u}\left(x_{jrt}, p_{jrt}, \sigma_h\right) = & \sum_{k=1}^{K} \sigma_h^k \text{nutrient}_{jrt} + \sigma_h^{sz} \text{size}_{jrt} \\ & + \sigma_h^{fl} \text{nflavor}_{jrt} + \sigma_h^p \text{p}_{jrt} + \sigma_h^{out} \text{const} \\ & + \beta^c \text{calorie}_{jrt} + \beta^o \text{organic}_{jrt} + \beta^s \text{sales}\end{aligned} \tag{10}$$

I allow for consumer taste heterogeneity on nutrition contents, container size, number of flavors, price, and the outside option. A consumer in a retailer-market-year is characterized by a d-vector of demographic variables which include income, household size, female head education. In addition to the idiosyncratic taste parameters σ, I specify linear parameters on calorie, organic, and number of sales.

The utility maximization problem and the logit assumption on ε_{jrht} give rise to predicted market shares for each product-retailer in a market:

$$s_{jrht}\left(\sigma_D, \xi, X, p\right) = \int \frac{\exp\left(X_{jrt}^1 \sigma_h + X_{jrt}^2 \beta + \xi_{jrt}\right)}{1 + \sum_{\{k\} \in A} \exp\left(X_{krt}^1 \sigma_h + X_{krt}^2 \beta + \xi_{krt}\right)} dF\left(\Sigma_D\right) \tag{11}$$

where A is the collection of products offered by the retailer less of j. X_{jrt}^1 is the set of product characteristics with random coefficients, and X_{jrt}^2 are the characteristics with linear parameters. $F(\Sigma_D)$ is retailer-market specific demographic distribution.

Quantify Quality of Product Placement. I parameterize the structural error term (ξ_{jrmt}) in the demand model according to Equation 12. The parameterization serves two goals: (1) to control for systematic components that are likely known to the firms at assortment design stage; (2) to separate and quantify the unobserved quality of product placement.

$$\xi_{jrmt} = \xi_{jt} + \xi_{brmt} + \Delta\xi_{jrmt} \tag{12}$$

The product-retailer-market-year level unobserved structural shock ξ_{jrmt} is decomposed into product-year fixed effects ξ_{jt} (a demand shock that is common to a product, for example, a product is popular in a year), and brand-retailer-market-year fixed effects ξ_{brmt}. These capture everything that varies at the brand-retailer-market level. Importantly, to the extent that a retailer gives better quality of product placement to a brand in the form of larger shelf space, more facings, eye-level display, or more in-store ads, this "preferential treatment" is absorbed into ξ_{brmt}. How much market share variation can be explained by ξ_{brmt} is indicative of how effective the vertical arrangement between a retailer and a brand is in shifting consumer demand.

Given this parameterization, $\Delta\xi_{jrmt}$ represents product-retailer-market-year unobservable deviations from the brand mean. Therefore, the identification assumption of the demand model is that $\Delta\xi_{jrmt}$ is not observed at assortment selection stage, and thus is independent from the observed product characteristics: $E[\Delta\xi_{jrmt}|X_{jrmt}] = 0$. This assumption is reasonable for two reasons: first, vertical contract is negotiated and signed at the brand-retailer level. If the captain (or retailer) chooses product assortments of all the brands within chain, this endogenous variation will be controlled for by ξ_{brmt};[17] second, conditioning on the consumer-product matching (captured by the random utility component), the unobserved product quality shock (ξ_{jt}), and the brand's unobserved quality of product placement (ξ_{brmt}), the variation remaining in $\Delta\xi_{jrmt}$ can be mainly interpreted as unobserved product demand shock.[18]

After model estimation, I retrieve $\hat{\xi}_{brmt}$ following the steps below:[19]

1. Calculate $\tilde{\xi}_{jrmt} = \hat{\delta}_{jrmt} - X_{jrmt}\hat{\beta}$, where $\hat{\delta}_{jrmt}$ is the estimated mean utility, $\hat{\beta}$ are estimated linear coefficients.[20]

2. Project $\tilde{\xi}_{jrmt}$ onto product-year fixed effect (γ_{jt}) and brand-retailer-market-year fixed effect (γ_{brmt}), and remove the product-year component from $\tilde{\xi}_{jrmt}$:

$$\tilde{\xi}_{jrmt} = \gamma_{jt} + \gamma_{brmt} + \varepsilon_{jrmt} \tag{13}$$

$\Rightarrow$

$$\hat{\xi}_{brmt} = \hat{\gamma}_{brmt}$$

In Equation 13, the reference retailer is set to be the largest retailer with the most

[17]Product choice is not modeled in this model, thus ξ_{brmt} does not capture product choice variation. An implicit assumption of my empirical analysis is that the captain (or retailer) chooses product composition first, and then the price and product placement (ξ_{brmt}). For the goal of this paper, which is inference analysis, it is sufficient to infer captaincy status using information and variation contained in ξ_{brmt} and prices.

[18]Industry practitioners confirm that contracts are negotiated at brand level with retailers. If category captain is biased toward its own brand, all products of this brand will receive a higher quality of product placement.

[19]To ease computation of the demand model, I perform a within-transform on mean utility δ_{jrmt}, instrumental variables Z_{jrmt} and the weighting matrix W, removing the product-year and retailer-brand-year fixed effects when forming the GMM objective function. Thus after the estimation, I need to retrieve ξ_{jrmt} and normalize it for subsequent analysis.

[20]$\delta_{jrmt} = X^2_{jrmt}\beta + \xi_{jrmt}$

brand-market coverage in that year. This helps normalize $\hat{\xi}_{brmt}$ across retailers of different sizes.

3. Normalize $\hat{\xi}_{brmt}$ by dividing by retailer size (log number of yogurt product sizes within the retailer).

Estimation. I use two sets of instrumental variables to address the endogeneity of price and market share (Berry and Haile 2014, Gandhi and Houde 2019). The first set of instruments, price instruments, include input costs interacted with product characteristics such as milk price $\times$ fat, plastic price $\times$ size, and sugar price $\times$ sugar; transportation costs such as diesel price $\times$ distance to the nearest factory, diesel price $\times$ size, and diesel price $\times$ rivals' average distance to the nearest factory; assortment variables such as number of UPCs, number of sizes; and a brand-retailer's main market demographic characteristics interacted with that brand's product characteristics.[21] This set of instruments serve as cost shifters or markup shifters.[22]

The second set of instruments—differentiation IVs—characterizes competition intensity each product faces within retailer. The base IVs are constructed following Gandhi and Houde (2019). I exploit variation in household demographics across retailer-markets and interact the mean and standard deviation of income, female education and number of kids with base differentiation IVs (see Appendix D for IVs used in the demand estimation and first stage price regressions).

The model is estimated using simulated GMM. I use nested fixed point algorithm proposed by Berry et al. (1995). Standard errors are clustered at retailer-brand level.

Demand Results. Table 8 shows estimation results from the demand model. The estimates are reported with cluster-robust standard error in parenthesis. The estimated parameters for price are intuitively signed: the positive price $\times$ income coefficient indicates that consumer price sensitivity decreases with income. The price sensitivity also decreases as female householders are more educated. Since yogurt nutrients are correlated with each other, the estimated taste coefficients for characteristics are a bit difficult to interpret. Consumers in general prefer low-sugar and low-fat yogurt. All else equal, households with more kids prefer more flavor options, larger container size, and lower fat, sugar and sodium options.

[21] The reason for using the last set of IVs is that the characteristics of the market where a brand has the highest share within a retailer, might be a factor that is taken into consideration in vertical contract negotiation, therefore affecting prices of products sold in other markets of the retailer, because of within-chain uniform pricing (DellaVigna and Gentzkow 2019).

[22] The intuition is that these costs of operation affect prices, but are not correlated with demand-side unobservables.

Furthermore, the assortment depth variable—number of flavors—plays an important role in explaining consumer demand and market share: the estimated random coefficients associated with number of flavors are large in magnitude and precisely estimated. Model implied own elasticity is negative for all the products. Median own-price elasticity is -5.129, which is comparable with other yogurt applications using BLP model (Hristakeva 2019, Berto Villas-Boas 2007).

Table 8: Demand Estimates from the Random-Coefficient Model

	Intercept	*Price*	*Sugar*	*Sodium*	*Fat*	*Size*	*# Flavors*	*Calorie*	*Organic*	*Sales*
Linear Parameters	-0.0048	-7.89	-0.0026	-0.086	0.090	0.041	2.78	0.011	0.091	0.370
	(0.001)	(4.83)	(0.105)	(0.026)	(0.248)	(0.076)	(1.08)	(0.003)	(0.152)	(0.023)
Non-linear Parameters										
× Income	-0.132	0.314	-0.036	0.751	-0.233	-1.045	-2.273			
	(0.905)	(0.44)	(0.09)	(0.25)	(0.27)	(0.70)	(0.98)			
× Number of Kids			-0.060	-1.601	-0.465	2.881	4.478			
			(0.42)	(0.69)	(1.98)	(0.85)	(1.41)			
× Female Education		0.408		-0.403	0.537					
		(0.35)		(0.38)	(0.50)					
Median & Mean Elasticity					-5.129 & -5.085					
% Own-price Elasticity > -0.1						0				

Notes: This table shows results from random coefficient demand model. Standard errors (clustered at retailer-brand level) in parentheses.

Table 9 examines the relationship between the estimated substitution patterns and competition intensity in the product space. I regress model implied diversion ratio (column (1)) or cross-price elasticity (column (2)) of product pairs on absolute characteristic differences between the two products, controlling for retailer, market and year fixed effects. The regression results confirm that the more similar two products are in the characteristic space, the larger the diversion ratio is.

Table 9: Relationship between Diversion Ratio, Elasticity and Characteristic Differences

VARIABLES	Diversion Ratio	Cross-Elasticity
Diff Calorie	0.000538***	-0.000480***
	(1.26e-05)	(7.83e-05)
Diff Fat	-0.000788***	-0.00537***
	(1.30e-05)	(8.10e-05)
Diff Organic	-0.00104***	-0.00718***
	(9.44e-06)	(5.87e-05)
Diff Sugar	-0.000521***	-0.00118***
	(7.11e-06)	(4.42e-05)
Diff Sodium	-0.00173***	-0.0125***
	(1.18e-05)	(7.32e-05)
Constant	0.00609***	0.0321***
	(7.49e-06)	(4.66e-05)
Observations	3,933,367	3,933,367
R-squared	0.099	0.043

Notes: This table reports results from regressions of diversion ratio and cross elasticity on absolute characteristic differences of product pairs. *** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.

Table 10 shows that product pairs that share the same fat level and size, are produced by the same company, or from the same product line have a larger diversion ratio. The diversion ratio between Dannon and Yoplait products is also significantly higher than product pairs between other brands in the data.

Table 10: Regression Results of Diversion Ratio on Same-product Indicator

	Diversion Ratio	Diversion Ratio	Diversion Ratio	Diversion Ratio
Same Fat Level	0.000409***			
	(7.84e-06)			
Same Size	0.000366***			
	(7.04e-06)			
Same Product Line		0.00124***		
		(1.52e-05)		
Same Company			0.00122***	
			(9.65e-06)	
Dannon-Yoplait Pair				0.00110***
				(1.15e-05)
Constant	0.00466***	0.00485***	0.00473***	0.00481***
	(4.99e-06)	(3.56e-06)	(3.76e-06)	(3.66e-06)
Observations	3,933,367	3,933,367	3,933,367	3,933,367
R-squared	0.089	0.089	0.091	0.090

Notes: This table shows results from regressing diversion ratio on indicator whether two products have the same fat level, size, are from the same product line (or company), and are Dannon and Yoplait. Each column represents one regression. All the regressions control for retailer, market and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1, standard errors in parentheses.

Interpretation of Brand-Retailer-Market-Year Fixed Effects. The brand-retailer-market-year fixed effects $\hat{\xi}_{brmt}$ is the structural error term identified by the demand model after the model controls for price endogeneity, observable demand factors (including observable assortment) and demographic variation across retailers and markets. In this section, I provide evidence to support that the estimated structural error term $\hat{\xi}_{brmt}$ is a proxy for the unobserved quality of product placement stemming from captaincy arrangements. In particular, I show that the variation in this term is mainly driven by the brand-retailer dimension, which suggests that it captures the extent to which the outcome of the vertical arrangement between the captain and retailer drives the demand.

Variance Decomposition on $\hat{\xi}_{brmt}$: To quantify the main source of variation in $\hat{\xi}_{brmt}$ across retailers and markets, I conduct a AKM decomposition on $\hat{\xi}_{brmt}$ (same as Equation 1) by projecting the estimated $\hat{\xi}_{brmt}$ onto brand × retailer fixed effect, brand × market fixed effect, market and retailer fixed effect, and calculating the percentage of variation in $\hat{\xi}_{brmt}$ that is accounted for by each component:

$$\hat{\xi}_{brm} = \gamma_r + \psi_{m(r)} + \gamma_{br} + \gamma_{bm} + \gamma_t + \varepsilon_{brm}$$

The results from the variance decomposition are presented in Table 11. The Brand × Retailer dimension explains the majority of the variation in $\hat{\xi}_{brmt}$, which mirrors the market share decomposition (Table 4). Notice that in the share decomposition, the Brand × Market dimension explains about 33% of the total variation in shares. But once I control for the observable demand factors across retailers and markets in the model, the variance in the Brand × Market term, which captures unobserved heterogeneity in tastes across markets, is further reduced to 8.9% (Table 11). Across both samples (all brands and Dannon and Yoplait), the brand × retailer variance is the largest, suggesting that the brand-retailer relationship plays an important role in explaining the asymmetry in brand market shares across retailers and markets.

Table 11: Variance Decomposition of $\hat{\xi}_{brmt}$

	All Brands		**Dannon and Yoplait**	
	Level	Percentage	Level	Percentage
Total	0.516	100	0.341	100
Brand × Retailer	0.439	85.16	0.306	89.81
Brand × Market	0.046	8.91	0.024	7.28
Residual	0.033	6.52	0.016	4.87
2Corr	-0.0082	-1.59	-0.00671	-1.97
R^2	0.934		0.951	
RMSE	0.239		0.161	

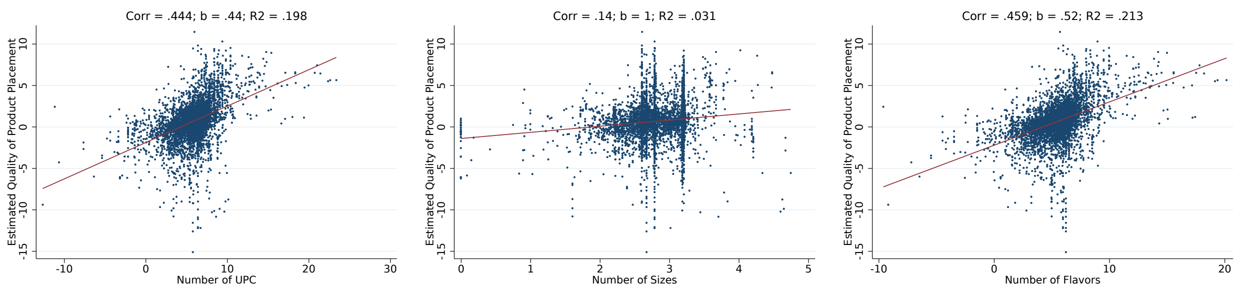
Notes: This table shows the level and percentage of variance of each component from the variance decomposition on $\hat{\xi}_{brmt}$.

Correlation of $\hat{\xi}_{brt}$ with Observed Assortment: If the captain controls shelf space allocation, then one would expect that the quality of product placement the brands gets will be positively correlated with their assortments such as number of UPCs, sizes, and flavors. To assess the strength of the estimated $\hat{\xi}_{brt}$ in capturing quality of product placement, I calculate the correlations between $\hat{\xi}_{brt}$ and the observed retailer-brand level product assortment variables.[23] Figure 3 and Figure 4 shows that the estimated quality of product placement $\hat{\xi}_{brt}$ is positively correlated with observable assortment variables such as number of UPCs, number of sizes, and number of flavors. Similar correlation exists between $\hat{\xi}_{brt}$ and number of sales, market share.

[23] I further aggregate the $\hat{\xi}_{brmt}$ to brand-retailer-year level.

Figure 3: Correlation between Estimated shelf advantage and Observed Assortment Depth

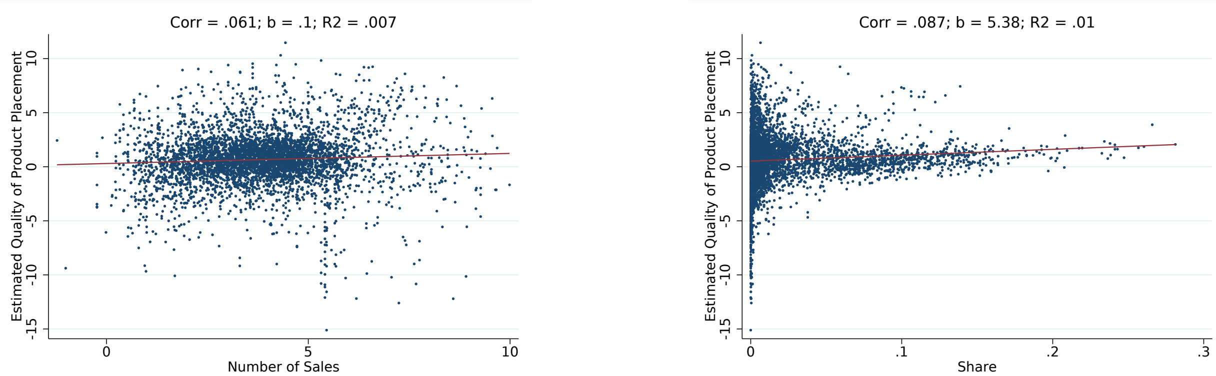
(a) $\hat{\xi}_{brt}$ and Number of UPCs (b) $\hat{\xi}_{brt}$ and Number of Sizes (c) $\hat{\xi}_{brt}$ and Number of Flavors



Notes: This figure depicts positive correlation between estimated shelf advantage ($\hat{\xi}_{brt}$) and observed brand-retailer level assortment variables including number of UPCs, number of sizes, and number of flavors.

Figure 4: Correlation between Estimated Quality of Product Placement and Observed Sales and Shares

(a) $\hat{\xi}_{brt}$ and Number of Sales (b) $\hat{\xi}_{brt}$ and Market Share



Notes: This figure depicts correlation between estimated shelf advantage ($\hat{\xi}_{brt}$) and observed brand-retailer level, number of sales and market share.

Persistence of $\hat{\xi}_{jrmt}$ over-time: As confirmed by industry practitioners, category captaincy is a long-term contract renewed at yearly basis. We should see a high correlation in $\hat{\xi}_{jrmt}$ over time if it captures this vertical component. To test this, I estimate a AR(2) regression on $\hat{\xi}_{jrmt}$. Results in Table 12 suggest that $\hat{\xi}_{jrm}(t)$ and $\hat{\xi}_{jrm}(t-1)$ are significantly positively correlated, which aligns with the institutional knowledge.

Table 12: Correlation of $\hat{\xi}_{jrmt}$ Over Time

	$\hat{\xi}_{jrm}(t)$
$\hat{\xi}_{jrm}(t-1)$	0.696***
	(0.00454)
$\hat{\xi}_{jrm}(t-2)$	0.226***
	(0.00467)
Constant	-0.00595
	(0.181)
Observations	52,804

Notes: AR(2) regression results on $\hat{\xi}_{jrmt}$ overtime. t = year.

The above evidence supports my interpretation that the brand-retailer-market fixed effects estimated from the demand model is a proxy for the quality of product placement: it largely explains unobserved demand asymmetries across retailers-markets, it is positively correlated with observed assortment variables, and it is persistent over time, which are consistent with our understanding of the captaincy practice. An intuitive way to interpret and understand the economic content behind this term is that it captures the "preference" that a retailer gives to a brand on the shelves, for example, larger shelf space, eye-level or end-of-aisle display, more in-store ads and promotions that induce profitable incremental manufacturer sales.

I finish this section with a discussion about other potential drivers of the variation in $\hat{\xi}_{brmt}$ that is not related to retailer-manufacturer relationship. Consumers may have an innate preference for a certain brand sold in a particular retailer—imagine an extreme case where every customer of Kroger prefers Dannon, while every customer of Walmart prefers Yoplait; or consumers like Dannon more in Kroger than in Walmart. If this is the case, then it will be absorbed in the $\hat{\xi}_{brmt}$. In Appendix D, I present a casestudy that there is no statistically significant difference in demographic characteristics of consumers who shop at retailers with different market share asymmetry patterns in the same market, which is indicative that this extreme case should not be a major concern. Furthermore, since Dannon and Yoplait are similar brands with largely overlapping product lines, and they are present in all the stores in the sample, from which retailer the consumers purchase these two brands should not significantly affect their utility. Thus, this match between consumers and retailers based on brand preference is less likely to be the main driver in $\hat{\xi}_{brmt}$. Another potential concern is that although the random coefficient components partly control for systematic differences in unobserved product characteristics (such as probiotics) for which tastes across retailers vary, the $\hat{\xi}_{brmt}$ might still capture some of it. It is less of a concern given that these two brands do not position themselves as "niche" brands, and the majority of retailers in Nielsen data are traditional retailers.

4.2 Retailer Classification

Using the estimated retailer-specific quality of product placement ($\hat{\xi}_{brmt}$), as well as fraction of UPCs directly calculated from the data, I classify the retailers into three types of captaincy arrangements: Dannon as the captain, Yoplait as the captain, and RCM (retailer category management). This classification step measures the prevalence of captaincy practice, and is important for the implementation of the second inference test—conduct test.

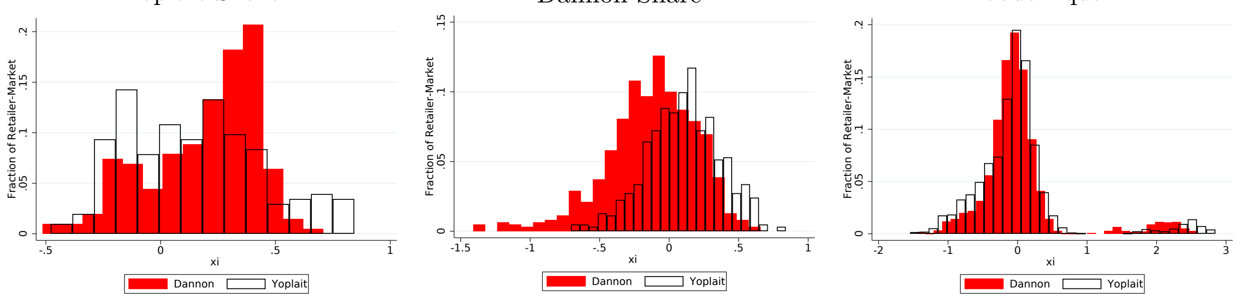
Figure 5 depicts distributions of $\hat{\xi}_{brmt}$ of Dannon and Yoplait across the three groups of retailers identified by market share asymmetry. The distributions of $\hat{\xi}_{brmt}$ display similar asymmetry between the top two brands as in market share and fraction of UPCs distributions (Figure 1 and Figure 2). The classification of retailers makes use of these distributional differences in the quality of product placement, especially the differences in the means of $\hat{\xi}_{brmt}$ for the top two brands across retailers. It is important to note that my classification methods will not rely on any information from the observed market shares. Rather, it is an entirely data-driven procedure that relies on information from the model estimated quality of product placement and the depth of product assortment.

Figure 5: Distributions of $\hat{\xi}_{brmt}$ of Dannon and Yoplait across Retailer Groups by Market Share Asymmetry

(a) Dannon Share Greater than Yoplait Share

(b) Yoplait Share Greater than Dannon Share

(c) Dannon and Yoplait Share About Equal



Notes: This figure shows distributions of $\hat{\xi}_{brmt}$ for Dannon and Yoplait across the three groups of retailers determined by market share asymmetry.

Based on these data patterns, I propose two classification rules: the first one is deterministic, the second one is stochastic. The preferred classification rule is the stochastic classification model, which allows for probabilistic decisions in classification. [24]

[24] Nevertheless, the two classification results largely overlap. And I incorporate the information from deterministic

Deterministic Classification. An intuitive and straightforward way to classify retailers is to compare the differences in means of $\hat{\xi}_{brmt}$ and n_{brmt} (fraction of UPCs) of Dannon and Yoplait, which yields the following classification rule.[25]

If $\bar{\xi}^{dn}$ - $\bar{\xi}^{yp} > 0$ & $\bar{n}^{dn}$ - $\bar{n}^{yp} > 0 \rightarrow$ Dannon-captained retailer (DN-CC)

If $\bar{\xi}^{dn}$ - $\bar{\xi}^{yp} < 0$ & $\bar{n}^{dn}$ - $\bar{n}^{yp} < 0 \rightarrow$ Yoplait-captained retailer (YP-CC)

If $\bar{\xi}^{dn}$ - $\bar{\xi}^{yp} > 0$ & $\bar{n}^{dn}$ - $\bar{n}^{yp} < 0$ (or the opposite signs) $\rightarrow$ RCM retailer

where superscript *dn* and *yp* denote respectively Dannon and Yoplait, and $\bar{n}_{brmt}$ denotes the mean across markets within a retailer for a given brand.

The first row of Table 14 reports the fraction of retailers classified into Dannon-captained (DN-CC), Yoplait-captained (YP-CC), and RCM.

This mean comparison rule, though straightforward, can suffer from mis-specifications. Since many observations between Dannon and Yoplait overlap in Figure 5, deterministic benchmarks can be arbitrary. Therefore, I apply a stochastic classification model which transforms the information on the quality of product placement and product assortment into a likelihood distribution of captaincy arrangements.

Stochastic Classification. I apply a Bayesian inference approach to the classification. The advantage of this approach is that it provides a unified treatment of inference and properly accounts for parameter and model uncertainty.

Finite Mixture Model. I treat the captaincy arrangement as a random variable that takes three distinct types (Dannon-captained, Yoplait-captained, and RCM), and model the data generating process of $\hat{\xi}_{brmt}$ and n_{brmt} using a finite mixture model (omitting subscripts *brmt* for ease of presentation):

$$g(\hat{\xi}, n) = \sum_{k=0}^{2} p_k f_k(\hat{\xi}, n \mid \Theta), \qquad \sum_{k=0}^{2} p_k = 1 \tag{14}$$

where $f_k(\hat{\xi}, n \mid \Theta)$ is the conditional likelihood of observing $\hat{\xi}$ and n given a type k: let $k = 0$ denote Dannon-captained type, $k = 1$ denote Yoplait-captained type, $k = 2$ denote RCM. Each retailer belongs to one of the three distinct types. p_k is the probability of each type. Θ is the set of parameters to be estimated in the type conditional likelihood.

The type conditional likelihood $f_k(\hat{\xi}, n \mid \Theta)$ is further modeled using linear regressions

classification results in my stochastic approach.

[25] The subscripts for retailer, market and year are omitted.

with shelf advantage parameters (β_1, β_2):

$$
\begin{aligned}
\hat{\xi}_{brmt} &= \gamma_0 + \beta_1 \mathbb{1}\{b = CC\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t + \epsilon_{1,brmt} \\
n_{brmt} &= \gamma_0 + \beta_2 \mathbb{1}\{b = CC\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t + \epsilon_{2,brmt}
\end{aligned} \tag{15}
$$

where $\mathbb{1}\{b = CC\}$ is an indicator for the captain brand within retailer r at market m (conditional on the type, we know which brand is the captain). γ_b, γ_r, γ_m and γ_t are respectively brand, retailer, market and year fixed effects, γ_0 is an intercept. The brand fixed effects absorb the national appeal of a brand. The retailer fixed effects control for unobserved retailer characteristics that can be correlated with captaincy choice. For each outcome variable, I estimate a shelf advantage parameter (β_1, β_2) for the captain brand (CC). The equations capture the fact that a captain brand within retailer r enjoys a "boost" in the quality of product placement and product assortment on the shelves.

With normal distributional assumption on $\epsilon_{1,brmt}$ and $\epsilon_{2,brmt}$, the posterior likelihood of $\hat{\xi}_{brmt}$ and n_{brmt} is expressed in Equation 16. It is a weighted average of three multivariate normal distributions with type specific means and variance-covariance matrix of the ϵ's (Σ_ϵ), with the probabilities of each type as weights:

$$
g(\hat{\xi}_{brmt}, n_{brmt} \mid \gamma) = \sum_{k=0}^{2} p_k N \left(\begin{bmatrix} \gamma_0 + \beta_1 \mathbb{1}\{b = k\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t \\ \gamma_0 + \beta_2 \mathbb{1}\{b = k\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t \end{bmatrix}, \Sigma_\epsilon \right) \begin{pmatrix} \hat{\xi}_{brmt} \\ n_{brmt} \end{pmatrix} \tag{16}
$$

where $\mathbb{1}\{b = k\}$ takes the value of 1 for the captain brand. (for example, it equals to 1 for all the Dannon observations if $k = 1$. It takes 1 for the other brands besides Dannon and Yoplait if $k = 0$).

This finite mixture model is a reduced-form method of modeling complex densities of assortment distributions in terms of a simple structure. The goal of the analysis is to estimate this multivariate normal mixture through its parameterization, by specifying and estimating the mean vectors, covariance matrix and relative probabilities.

Identification. In Equation 15, statistical independence between the residuals (ϵ_{brmt}) and the captain brand dummy is needed for consistent estimation of βs. Therefore, I maintain an identification assumption that the captaincy types is independent of the residuals. There are concerns one might have about this exogeneity assumption. First, captain selection is endogenously made by the brand and the retailer. If there is unobserved heterogeneity in tastes across retailers for a particular brand left in $\hat{\xi}_{brmt}$, and the retailer decision is based on it, then this leads to a simultaneity problem. I provide arguments at the end of subsection 4.1 to suggest that the consumers matching with retailers based on brand preference is a secondary concern. Second, captain selection is assumed to be made before the demand shocks are realized, thus less likely to be strongly correlated with unobserved taste differences across markets.

In terms of data structure and variation, identification of the mixing probabilities and the component distributions relies on several sources: first of all, the main source of identifying power is the panel structure of $\hat{\xi}_{brmt}$ and n_{brmt}. That is, I observe the same brand-retailer pair repeatedly across markets and time. βs capture consistently higher shelf advantage of a particular brand across all the markets and years within the same retailer, compared with the average market-level shelf advantage. Second, the assumption that vertical contracts affect both outcomes (quality of product placement and product assortment) places cross-equation restriction on shelf advantage parameters. Third, the assortment variables respond differently to changes in captain identity for different types. In addition, the parametric assumption that there are three distinct types, and the functional form assumptions on the conditional type likelihood — that it is linear, and the coefficients βs are the same across the mixture types — also helps the identification.[26]

I use Gibbs sampler, a Markov chain Monto Carlo (MCMC) algorithm from Bayesian inference methods, to approximate the posterior mixture distribution and estimate the parameters.

Gibbs Sampler Algorithm. The parameters to be estimated from Equation 16 are $\Theta = (\beta_1, \beta_2, \Sigma_\epsilon)$ and the type probabilities p. In the Bayesian paradigm, each parameter is considered as a random variable with its own distribution. Starting from an initial knowledge described in the prior distribution of the parameters, the Bayesian inference method updates this information by adding information from the data. Following the literature (Rossi et al. 2012, Viele and Tong 2002, Lee et al. 2016), a standard prior structure for probabilities p and parameters Θ is:

$$p \sim \text{Dirichlet}\left(\alpha_0, \alpha_1, \alpha_2\right)$$
$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{\beta_1} \\ \mu_{\beta_2} \end{pmatrix}, \quad \Sigma_\beta\right)$$
$$\Sigma_\epsilon \sim \text{InvWishart}\left(a_1, a_2\right)$$

[26] These assumptions are justified by institutional knowledge and data evidence. Recall the distributions of n_{brmt} and $\hat{\xi}_{brmt}$ (Figure 2 and Figure 5), the main difference between groups is the location of the means, which can be properly approximated by linear regressions with mean shifters. The same βs across different types can be somewhat restrictive. However, the data distributions do not exhibit outlier clusters of big variance, which means that the same regression plane implied by the same βs can fit the data well.

where $p = (p_0, p_1, p_2)$ are probabilities of each type. α_k, a_1 and a_2 are hyper-parameters.

To enable Bayesian update and inference, I introduce an unobserved *latent variable* $z_r \in \{0, 1, 2\}$ into the model. z_r is a vector of assignments to each retailer of a type that generates $\hat{\xi}$ and n. The purpose of augmenting the data with z_r is to remove the finite mixture structure from the observed sample. This allows for simulation of the shelf advantage parameters, conditional on the assignments of observations allocated to each particular type. Then with the simulated shelf advantage parameters, the assignments (latent variable z_r) are updated using Bayes Rule. This suggests an iterative algorithm described below:

Stack up the two regressions in Equation 15 into one large regression:

$$y = X\beta + \epsilon, \qquad \epsilon \sim N(0, \Sigma_\epsilon \otimes I_n)$$

with

$$y = (\hat{\xi}, n), \quad X = \begin{bmatrix} \Gamma & 0 \\ 0 & \Gamma \end{bmatrix}, \quad \beta = (\beta_1, \beta_2)', \quad \epsilon = (\epsilon_1, \epsilon_2)$$

where Γ is a matrix collecting the indicator for captain brand, and all the fixed effects, as well as the intercept in the linear regressions.

Gibbs sampler iterates through the following steps:[27]

1. Draw $z_r \sim Multinomial$

$$\left(\frac{p_0 N(\mu_0, \Sigma_\epsilon)}{\sum_k p_k N(\mu_k, \Sigma_\epsilon)}, \quad \frac{p_1 N(\mu_1, \Sigma_\epsilon)}{\sum_k p_k N(\mu_k, \Sigma_\epsilon)}, \quad \frac{p_2 N(\mu_2, \Sigma_\epsilon)}{\sum_k p_k N(\mu_k, \Sigma_\epsilon)} \right)$$

$$\text{where } N(\mu_k, \Sigma_\epsilon) = \prod_{i \in r} N\left(\begin{bmatrix} \gamma_0 + \beta_1 \mathbb{1}\{b = k\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t \\ \gamma_0 + \beta_2 \mathbb{1}\{b = k\} + \gamma_b + \gamma_r + \gamma_m + \gamma_t \end{bmatrix}, \Sigma_\epsilon \right) \begin{pmatrix} \hat{\xi}_i \\ n_i \end{pmatrix}$$

2. Draw

$$p \sim \text{Dirich}\left(\alpha_0 + \#(z_r = 0), \alpha_1 + \#(z_r = 1), \alpha_2 + \#(z_r = 2)\right)$$

3. Draw

$$\Sigma_\epsilon \sim InvWishart\left(a_1 + \frac{1}{2}\epsilon' * \epsilon, \quad a_2 + \frac{N}{2}\right)$$

[27] To ease presentation, I use i to denote the level of observation: brand-retailer-market-year.

4. Draw

$$\beta \sim N\left((X'X)^{-1}(X'y + \Sigma_\epsilon^{-1}\bar{\beta}), \Sigma_\epsilon(X'X + \Sigma_\epsilon^{-1})^{-1}\right)$$

In the estimation, the hyper-parameters are set to be: $\alpha_k = 1$, $a_1 = \begin{bmatrix} 0.35, 0.001 \\ 0.001, 0.35 \end{bmatrix}$, $a_2 = 0.01$.[28] $\bar{\beta}$ is the prior of the means of β, which are set to be (0,0).[29] The starting values for the probability of each type are uniform. The sample is further aggregated to three brands (Dannon, Yoplait, and other brand). The regressions are estimated using residualized variables from which all the fixed effects are demeaned. I initiate the Markov chain from different starting points of p_0, β_0, and Σ_0 and it converges to the same optimal point. In sensitivity checks, the results remain robust to different sets of hyper-parameters.

Classification Results. In this subsection, I report the parameter estimates from Gibbs Sampler and the classification results. Then I discuss the retailer characteristics of the classified types of retailers, as well as the market structure in terms of captaincy arrangements. *Gibbs Sampler Estimates.* Table 13 shows the estimation results from Gibbs sampler. I report summary statistics from the estimated posterior distribution of each parameter, after removing a burn-in period (the first 1,000 iterations). The chain converges to the global optimum, and the estimated standard deviations are small (Appendix E provides diagnostics on the chain convergence property). The estimated shelf advantage parameters β_1 and β_2 are positive, which indicates that the captain brand receives a boost in the quality of product placement, and an increase in number of UPCs on the shelves.

Table 13: Gibbs Sampler Classification Results

	Prob(DN-CC)	Prob(YP-CC)	Prob(RCM)	β_1	β_2	Σ_ϵ
Mean	0.416	0.336	0.248	0.099	0.073	$\begin{pmatrix} 0.0835 & \\ 0.0009 & 0.0018 \end{pmatrix}$
Median	0.416	0.335	0.247	0.099	0.073	$\begin{pmatrix} 0.0835 & \\ 0.0009 & 0.0018 \end{pmatrix}$
Standard Deviation	0.029	0.027	0.026	0.0138	0.0018	

Notes: This table reports the estimation results from Gibbs sampler.

[28]This is a nearly non-informative prior since a_2 is small. a_1 is the variance-covariance matrix between $\hat{\epsilon}_{1,brmt}$ and $\hat{\epsilon}_{2,brmt}$ estimated from Equation 15 using the deterministic classification results.

[29]Based on institutional knowledge and distributions of $\hat{\xi}_{brmt}$ and n_{brmt}, I specify the priors of the shelf advantage parameters to be non-negative. This prior information also helps solve the 'label switching problem' caused by symmetric modes of likelihood for normal mixtures (Rossi et al. 2012).

Table 14 reports the classification results from both deterministic and stochastic rules. The fraction of retailers that potentially use category captain arrangement is relatively large (about 60% to 70%). Based on my interviews with industry practitioners, this fraction is in line with their knowledge of the prevalence of category captaincy.

Table 14: Retailer Classification

	Description	*Dannon-Captained*	*Yoplait-Captained*	*RCM*
Deterministic Classification	Mean Diff	0.23	0.43	0.35
Stochastic Classification	Gibbs sampler	0.42	0.33	0.25

Notes: The deterministic classification rule compares mean differences in $\hat{\xi}$ and number of UPCs of Dannon and Yoplait. The stochastic classification rule uses Gibbs sampler. For deterministic classification, I report the fraction of retailers belonging to each type. For Gibbs sampler, I report the estimated probabilities of each type.

Asymmetries in Retailers with a Captaincy Arrangement. An interesting question to ask, is whether the price, share and product assortment patterns in retailers classified to have a captain, also exhibit asymmetry between the captain brand and other brands. To examine this, I estimate Equation 17 on the group of classified retailers with a captaincy arrangement. In the equation, the difference in probabilities $\text{Diff\_Prob}_r = \text{Prob(DN-CC)}_r - \text{Prob(YP-CC)}_r$, $\text{Diff\_X}_r = X_r^{DN} - X_r^{YP}$ are assortment differences between Dannon and Yoplait at the retailer level (e.g. ξ Diff is $\bar{\xi}_r^{DN} - \bar{\xi}_r^{YP}$).

$$\text{Diff\_Prob}_r = \alpha + \beta \text{Diff\_X}_r + \epsilon_r \tag{17}$$

The results are shown in Table 15. In the classified retailers with a captain, a higher estimated probability with Dannon as the captain is correlated with a higher market share of Dannon, bigger assortment of Dannon products (measured by number of UPCs, number of sizes, number of flavors), and more sales on Dannon products. Moreover, the results in Column (7) suggest that the price difference between Dannon and Yoplait is smaller in Dannon-captained retailers than in Yoplait-captained retailers (recall that Dannon's average price is higher than Yoplait). This asymmetry in prices between Dannon and Yoplait, varying with the captain identity, provides important data variation for identifying asymmetry in markups and discriminating among conduct models (section 5). Table F3 in Appendix F shows similar results for regressions using differences in price (assortments) between Dannon and all the other brands within retailer as independent variables, suggesting that the price difference between Dannon and all the other non-captain brands is smaller in Dannon-captained retailers.

Table 15: Asymmetry in Shares, Assortments and Prices between Dannon and Yoplait in Classified Retailers with Captaincy Arrangement

	Dependent Variable: Prob (DN-CC) - Prob (YP-CC)						
Diff Dannon - Yoplait							
$\hat{\xi}$	1.633***						
	(0.212)						
Share		10.15***					
		(0.893)					
Fraction UPC			6.416***				
			(0.286)				
# of Sizes				1.367***			
				(0.323)			
# of Flavors					0.185***		
					(0.0292)		
# of Sales						0.0384***	
						(0.0134)	
Price							-1.242***
							(0.404)
Constant	0.233***	0.301***	0.362***	0.158**	0.669***	0.108	0.406***
	(0.0617)	(0.0555)	(0.0381)	(0.0671)	(0.115)	(0.0665)	(0.134)
Observations	225	225	225	225	225	225	225
R-squared	0.211	0.367	0.692	0.074	0.152	0.035	0.041

Notes: Each column is a separate regression of estimated probability difference ($Pr(DN-CC)-Pr(YP-CC)$) on differences in product assortment variables ($X^{DN} - X^{YP}$).

An anti-trust concern about category captaincy arrangement is the potential competitive exclusion from the captain toward its rivals, especially smaller brands. To test whether the retailers with a captain carry less variety of smaller brands (brands whose national market share are ranked below 25th), I estimate Equation 18 on the classified sample of retailers with a captain. y_{st} include number of small brands, number of small brands' UPCs, and number of small brands' products at the store-year level. $log(N_{st})$ is logged total number of UPCs at the store (across all the categories), as a proxy for store size. Table 16 shows the results: the classified retailers with a captain carry less variety of smaller brands than the retailers without a captain, after controlling for store size.

$$y_{srmt} = \alpha_0 + \beta_2 \mathbb{1}\{\text{store} \in \text{captained retailer}\} + \alpha_2 log(N_{st}) + \gamma_m + \varepsilon_{srmt} \tag{18}$$

Table 16: Variety of Small Brands in Captained Retailers is Lower than RCM Retailers

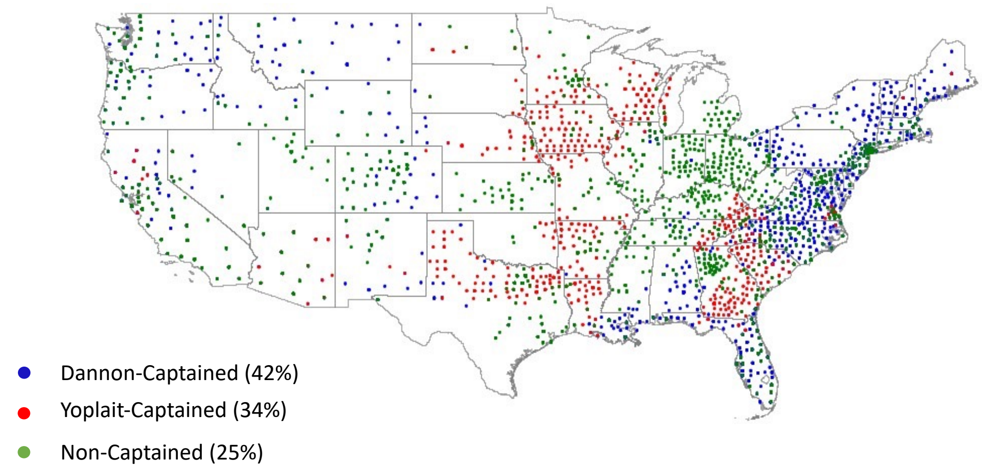
	Number of Brands	Number of UPCs	Number of Products
$\mathbb{1}\{\text{store} \in \text{captained retailer}\}$	-1.109***	-5.836***	-1.057***
	(0.0699)	(0.318)	(0.0711)
$log(N_{st})$	2.531***	12.32***	2.560***
	(0.0719)	(0.327)	(0.0731)
Constant	-21.54***	-106.8***	-21.82***
	(0.768)	(3.489)	(0.781)
Observations	7,999	7,999	7,999
R-squared	0.424	0.489	0.422
Average across stores	4.12	18.20	4.26

Notes: This table reports regression results from Equation 18. Each column is a regression with a different dependent variable. Standard error in parenthesis.

Appendix F presents more details on characteristics of the classified retailers. The RCM retailers tend to be bigger in size (measured by total number of UPCs across all categories, total revenue of the retailer, number of stores of the retailer), and carry more store brands (Table F2). I also find that the predicted type of each retailer is persistent across years, which is in line with industry knowledge and suggests that the Gibbs sampler provides meaningful classification (Table F1).

Market Structure in terms of Captaincy Types. Turning to market structure, Figure 6 plots the geographic distribution of the classified types of retailers. Each dot represents a store, and each color represents a captaincy type (blue is Dannon-captained, red is Yoplait-captained, and green is RCM). RCM retailers are present in 92% of DMAs. Furthermore, as shown in Table 17, the most common market structure is the markets with all three types of retailers (41.03%), followed by markets with Dannon-Captained and RCM (32.88%) and markets with Yoplait-Captained and RCM (15.84%). Table 18 zooms in to market type 2 where Dannon-captained and RCM retailers coexist, and market type 3 where Yoplait-captained and RCM retailers are both present, and summarizes market shares and fraction of UPCs of Dannon and Yoplait in the different types of retailers. I find that in RCM retailers in these markets, Dannon and Yoplait equally split market shares, while significant within-chain market share asymmetries exist in the captained retailers within the same region. This confirms that the market share asymmetries are not completely driven by the market-specific demand preferences.

Figure 6: Geographic Distribution of the Classified Types of Retailers



Notes: This figure depicts geographic distribution of the three types of retailers based on Gibbs sampler results in 2016. Each dot is a store. Blue dot represents Dannon-Captained retailers, red dot represents Yoplait-Captained retailers, and green dot represents RCM retailers.

Table 17: Percent of Markets (DMAs) with Mixed Captaincy Types

Market Type	Dannon-Captained	Yoplait-Captained	RCM	Percentage (by frequency)	Percentage (weighted by number retailer)
1	✓	✓	✓	29.34	41.03
2	✓		✓	35.33	32.88
3		✓	✓	19.16	15.84
4	✓	✓		5.39	4.52
5			✓	5.99	3.17
6	✓			3.59	1.96
7		✓		1.2	0.6

Notes: This table summarizes the percentage of markets (defined by DMA) that have different retailer captaincy types. Percentage (by frequency) is the percentage calculated with simple counts. Percentage (weighted by number retailer) is the percentage of markets weighted by the market size, proxied by total number of retailers in the market.

Table 18: Share and Assortment of Dannon and Yoplait in *Market Type 2* and *Market Type 3*

	Market Type 2				*Market Type 3*			
Retailers	Dannon-Captained		RCM		Yoplait-Captained		RCM	
	Share	Fraction UPCs	Share	Fraction UPCs	Share	Fraction UPCs	Share	Fraction UPCs
Dannon	0.33	0.29	0.22	0.16	0.25	0.21	0.26	0.17
Yoplait	0.24	0.23	0.23	0.21	0.43	0.38	0.28	0.23

Notes: This table summarizes market share and product assortment (fraction of UPCs) of Dannon and Yoplait in market type 2, where Dannon-captained and non-captained retailers coexist, and in market type 3, where Yoplait-captained and non-captained retailers coexist.

There are several implications from the market structure and geographic distribution patterns. Earlier findings by Bronnenberg et al. (2007), Hwang et al. (2010), Hwang and Thomadsen (2016) highlight the importance of persistent geographic variation in market shares of national brands, and follow-up papers by Bronnenberg et al. (2009) and Bronnenberg et al. (2012) provide possible explanations for this phenomenon, such as consumer preference and "early entry" advantage. My finding suggests that the heterogeneity across chains is equally important, and this heterogeneity is caused by strong asymmetries in how brands are presented on grocery shelves across retailers. Category captaincy arrangement is a possible explanation for the cross-market dispersion patterns documented in the aforementioned papers.

The Gibbs sampler also generates 10,000 matrices, each of which is an assignment matrix (dimension of the matrix = number of retailers $\times$ 3) that assigns each retailer into a different type, for that particular iteration. They will be incorporated in the second inference test—conduct tests discussed in the next section.

5 Inference Test Two—Pricing and Markups

The second inference test implied by the stylized supply model in subsection 3.4 is that the category captain introduces asymmetry in pricing and margins across brands within retailer. Specifically, the captain eliminates double marginalization from its own products, while the non-captain's products still have double marginalization. From Table 15 we also find that the captain brand enjoys a lower price in retailers where it is the captain than in retailers where it is not the captain—a data pattern that is in line with the captain pricing model. This section discusses the idea behind and the implementation of this inference approach.

Conventionally one can apply the conceptual framework and econometric tools developed in vertical relationship literature (Rivers and Vuong 1988, Berto Villas-Boas 2007, Bonnet and Dubois 2015), to conduct tests between the captain pricing hypothesis and other pricing hypotheses. The empirical challenge is that there exists significant heterogeneity in vertical contracts (in my setting, the captaincy arrangements) across retailers which needs to be taken into account in the conduct tests. Without knowing the captaincy arrangements, the conventional menu approach will result in 3^{88} pair-wise comparisons for just one year of the sample, which is computationally prohibitive.[30] Furthermore, since the presence of category captain contracts is latent, the distribution of contracts under the null hypothesis must be treated as a random variable. The first inference test makes the conduct tests feasible: the classification matrix produced in one iteration is one realization of the random variable of captaincy contract. This means I can account for the latent captaincy contracts by drawing repeatedly from the posterior distribution of the Bayesian classification. In other words, I can construct the test by simulating plausible arrangements given by the classification, and then averaging over thousands of draws to reduce the "measurement error" possibly caused by mis-classification.

5.1 Supply Side Models and Conduct Test

Supply Side Models. I focus on the case where the relationship between the retailer and the captain tries to address the traditional double marginalization problem, but only for the captain's products. Several alternative stylized vertical relationship models commonly considered in the literature can be formulated and tested against this null model. Consistent with the simple supply model, I present in this subsection the supply models under category captain scenario and RCM scenario. The empirical tests take into account more alternative pricing models.

(1) Category Captain (CC) Scenario:

The category captain chooses p_j(price), ξ_b(proxy for the quality of product placement) for all the products within the category for the retailer.[31] When it makes pricing and product placement decisions, it internalizes the business stealing patterns between its own products and the non-captain rival products.

$$\max_{p_j,\xi_b} \phi^{cc} \left(\sum_{j \in J_r^{CC}} (p_j - c_j) \sum_{\forall m: j \in m} s_{jm} + \sum_{j \in J_r^{NC}} (p_j - w_j) \sum_{\forall m: j \in m} s_{jm} - \gamma^{cc} (\sum_{b \in J_r} \xi_b) \right) \tag{19}$$

[30] 3 is the number of possible captaincy arrangements, 88 is the total number of retailers in 2016.

[31] I assume uniform pricing within chain (DellaVigna and Gentzkow 2019), hence the profits are summed over markets.

$$FOC(p_j^{CC}, j = CC): \qquad \sum_m s_{jm} + \sum_{k \in J_r^{CC}} (p_k - c_j) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial p_{jm}} + \sum_{k \in J_r^{NC}} (p_k - w_k) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial p_{jm}} = 0$$

$$FOC(p_j^{NC}, j = NC): \qquad \sum_m s_{jm} + \sum_{k \in J_r^{CC}} (p_k - c_j) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial p_{jm}} + \sum_{k \in J_r^{NC}} (p_k - w_k) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial p_{jm}} = 0$$

$$FOC(\xi_b): \qquad \sum_{k \in J_r^{CC}} (p_k - c_k) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial \xi_b} + \sum_{k \in J_r^{NC}} (p_k - w_k) \sum_{\forall m: k \in m} \frac{\partial s_{km}}{\partial \xi_b} = \gamma^{cc}$$

where subscript j = product, r = retailer, m = market, b = parent brand; superscript CC = captain product, NC = non captain product; J_r = set of products within chain; J_r^{CC} = set of CC products within chain; J_r^{NC} = set of non-CC products within chain.

I solve for equilibrium p and γ^{cc} in matrix terms, adding econometric error term ε to the pricing FOCs, u to the assortment FOC, and parameterizing marginal cost c into $x_1\beta_1$, where x_1 are cost variables including milk price × fat, sugar price × sugar, plastic price × size, diesel price × distance, diesel price × size, and distance × size, as well as retailer, brand, year fixed effects, and captain brand × retailer fixed effects. The captain brand × retailer fixed effects control for the possibility that captain status may change the retailer's marginal costs.[32]

$$\begin{cases} \mathrm{p}^{cc} &= \underbrace{c^{cc}}_{x_1^{cc}\beta_1} + \underbrace{\left[(T^{11} \cdot \Delta^{11}) - (T^{21} \cdot \Delta^{21})(T^{22} \cdot \Delta^{22})^{-1}(T^{12} \cdot \Delta^{12})\right]^{-1} \left[(T^{21} \cdot \Delta^{21})(T^{22} \cdot \Delta^{22})^{-1} s^{nc}(p) - s^{cc}(p)\right]}_{\text{retail margin}} + \varepsilon \\ \mathrm{p}^{nc} &= \underbrace{c^{nc}}_{x_1^{nc}\beta_1} + \underbrace{\left[(T^{22} \cdot \Delta^{22}) - (T^{12} \cdot \Delta^{12})(T^{11} \cdot \Delta^{11})^{-1}(T^{21} \cdot \Delta^{21})\right]^{-1} \left[(T^{12} \cdot \Delta^{12})(T^{11} \cdot \Delta^{11})^{-1} s^{cc}(p) - s^{nc}(p)\right]}_{\text{retail margin}} - \underbrace{\left(T_m^{22} \cdot \Delta^{22}\right)^{-1} s^{nc}}_{\text{wholesale margin}} + \varepsilon \\ \gamma^{cc} &= (p^{cc} - c^{cc}) \frac{\partial s^{cc}}{\partial \xi} + (p^{nc} - w^{nc}) \frac{\partial s^{nc}}{\partial \xi} + u \end{cases} \tag{20}$$

For matrices T and Δ, I use superscript 1 for CC products, 2 for non-CC products. Ts are ownership matrices. In particular, element (j, k) of T^{11} is equal to 1 if both products j and k are captain's products, element (j, k) of T^{12} is equal to 1 if product j is non captain's product and k is captain's product. Δs are response matrices, containing the first derivatives of shares with respect to retail prices ($\sum_m \partial s_{km}/\partial p_{jm}$), depending on which products belong to the captain or non captain. For example, Δ^{11} contains the first derivatives

[32] Only the pricing equations are used in conduct tests. The FOCs of ξ_b can be used for solving the shelf management costs and the first stage of the supply model, but empirical estimation of the first stage of the supply model is out of the scope of this paper.

of the captain products' shares with respect to the captain products' prices, Δ^{12} contains the first derivatives of the captain products' shares with respect to the non captain products' prices. T_m^{22} is the manufacturer ownership matrix for non-captain products.

(2) RCM Scenario: the retailer chooses p_j, ξ_b for all the products within the category.

$$\max_{p_j,\xi_b} \sum_{j\in J_r} (p_j - w_j) \sum_{\forall m: j\in m} s_{jm} - \gamma^{rcm} (\sum_{b\in J_r} \xi_b) \tag{21}$$

$$FOC(p_j): \qquad \sum_m s_{jm} + \sum_{k\in J_r} (p_k - w_k) \sum_{\forall m: j\in m} \frac{\partial s_{km}}{\partial p_j} = 0$$

$$FOC(\xi_b): \qquad \sum_{k\in J_r} (p_k - w_k) \sum_{\forall m: k\in m} \frac{\partial s_{km}}{\partial \xi_{bm}} = \gamma^{rcm}$$

Solve for equilibrium p and γ^{rcm} in matrix form:

$$\begin{cases} p^{rcm} = w^{rcm} - (T_r \cdot \Delta_r)^{-1} s^{rcm} + \varepsilon \\ \gamma^{rcm} = (p^{rcm} - w^{rcm}) \frac{\partial s^{rcm}}{\partial \xi} + u \end{cases} \tag{22}$$

where T_r is retailer's ownership matrix with element (i,j) equal to 1 if both products i and j are sold by the retailer. The response matrix ($\Delta_r = \sum_m \Delta_{rm}$) contains the first derivatives of all the shares with respect to retail prices. w^{rcm} is the solution from manufacturer's profit maximization problem, where T_w is wholesaler ownership matrix analogously defined as T_r:

$$w^{rcm} = c - (T_w \cdot \Delta_r)^{-1} s^{rcm} = x_1\beta_1 - (T_w \cdot \Delta_r)^{-1} s^{rcm}$$

With valid instruments, the pricing equations in Equation 20 and Equation 22 can be turned into testable moment conditions which will be used in the conduct tests. Next I will briefly describe the canonical conduct test approach and how I adapt it to my setting where vertical contracts vary across retailers.

Conduct Test. The goal of the conduct test is to discriminate among alternative pricing models and determine the one that fits the data best. I follow a non-nested hypothesis testing approach (Sudhir 2001, Rivers and Vuong 1988, Berto Villas-Boas 2007, Bonnet and Dubois 2015). Rivers-Vuong test (RV test) makes use of the pricing equations predicted by different supply side models (e.g. Equation 20 and Equation 22), and infers which model fits the data best based on lack-of-fit criterion: given any two competing models (g and h), the null hypothesis is that the two non-nested models are asymptotically equivalent:

$$\mathrm{H}_0: \quad \bar{Q}_n^g = \bar{Q}_n^h \tag{23}$$

where $\bar{Q}_n^g$ (resp. $\bar{Q}_n^h$) is the expectation of a lack-of-fit criterion Q_n^g (resp. Q_n^h) in the population. The lack-of-fit is defined via the GMM objective function, that is, the sample analogue of Equation 24 where Z is a set of IVs:

$$E[Z_{jr}\varepsilon_{jr}] = 0 \tag{24}$$

Letting $\hat{Q}_n^g$ and $\hat{Q}_n^h$ denote sample lack-of-fit criterion evaluated for model g (resp. h), the test statistic is

$$T_n = \frac{\sqrt{n}}{\hat{\sigma}^{gh}}\left(\hat{Q}_n^g - \hat{Q}_n^h\right) \tag{25}$$

where $\hat{\sigma}^{gh}$ is the estimated value of the variance of the difference in lack-of-fit. Rivers and Vuong (2002) show that the asymptotic distribution of T_n is standard normal under the null.

Incorporate Classification: To allow for heterogeneity in captaincy arrangement across retailers, I incorporate the results from the classification. Each iteration from the Gibbs sampler generates a set of possible captaincy arrangements (i.e. a subset of captained retailers, and a subset of RCM retailers). Given a classification matrix Z, I calculate RV test statistics, using the pricing equations corresponding to the captaincy status of the retailers and consistent with the hypotheses in question. Then I average across all the iterations to get the final test statistics. This approach explicitly accounts for possible mis-classification and reduces the impact of measurement error from the classification.

Alternative Pricing Models: I formulate a menu of pricing models based on different behavioral assumptions between retailers and manufacturers. The null model is the captain pricing model (H(0)). The alternative models differ in two aspects: which party (whether it is the retailer or the captain brand) sets the retail prices, and how margins are imposed (e.g. whether there is retail margin, or wholesale margin, or both). The alternative models are listed below:

H(0) Null Model (captain pricing): In retailers with a captain, the captain chooses retail prices for all the products within the category. It eliminates double marginalization from its own products by setting the wholesale margins to zero, and it imposes double markups on non-captains' products. In RCM retailers, the retailer sets retail prices for all the products based on linear pricing. This model is the empirical counterpart of the stylized theoretical model outlined in subsection 3.4.

H(1) Linear pricing (All DM): In retailers with a captain, it is still the retailer that chooses retail prices for all the products, imposing double marginalization on all the products. The manufacturers choose wholesale prices. In RCM retailers, the retailer sets retail prices for all the products based on linear pricing.

H(2) Zero wholesale margin (All zero WPCM): In retailers with a captain, the retailer chooses prices for all the products, given that wholesale prices are equal to marginal costs. In RCM retailers, the retailer sets retail prices for all the products with zero wholesale margin as well.

H(3) Zero retail margin (All zero RPCM): In retailers with a captain, the retailer chooses retail prices for all the products, setting the retail price-cost margins to zero for all the products. In RCM retailers, the retailer sets retail prices for all the products with zero retail margin as well.

H(4) No double marginalization for Dannon or Yoplait (DN & YP no DM): In retailers with a captain, the captain chooses retail prices for all the products: it eliminates double marginalization on both Dannon's and Yoplait's products, while imposing double marginalization on all the other products. This hypothesis is a possible equilibrium outcome from a multi-market contact collusion model (Bernheim and Whinston 1990). In RCM retailers, the retailer sets prices for all the products based on linear pricing.

H(5) Collusion between the captain and retailer (CC & retailer collude): In retailers with a captain, the retailer sets retail prices for all products. The retailer behaves as a vertically integrated firm with respect to the captain brand. It eliminates the wholesale margin of the captain's products, whereas the other products have double marginalization. In RCM retailers, the retailer sets retail prices for all the products based on linear pricing.

Table 19 summarizes all the alternative pricing models. The captain pricing model has two distinctive features that give rise to the captain's price advantage: first, the captain decides retail prices for all the products within the category. It internalizes business stealing patterns between its own products and its rivals' products; second, the captain eliminates double marginalization from its products and imposes double markups on its rivals' products. H(1) to H(3) are models most commonly considered in vertical relationship literature. A common feature of H(1) to H(3) is that retail pricing is symmetric: the retailer makes pricing decisions, and on which party in the supply chain to add/remove margin is the same across all the products, no matter whether there is a captain or not. H(4) and H(5) introduce some asymmetry into retail pricing: in H(4), the captain makes pricing decisions. H(5) has the same markups arrangement as the null model, but it is the retailer that sets retail prices instead of the captain. Therefore, the substitution patterns among all the products in the category are internalized under H(5).

Table 19: Alternative Pricing Models Tested in the Conduct Tests

Hypothesis	Pricing Decision	Margins
H(0) Captain Pricing Model	CC retailer: captain RCM retailer: retailer	CC retailer: captain products no double marginalization (DM), non-captains: DM RCM retailer: all products have double marginalization
H(1) All DM	retailer	all products: have double marginalization
H(2) All zero WPCM	retailer	all products: zero wholesale margin
H(3) All zero RPCM	retailer	all products: zero retail margin
H(4) DN & YP no DM	CC retailer: captain RCM retailer: retailer	CC retailer: Dannon & Yoplait no double marginalization (DM), non-captains: DM RCM retailer: all products have double marginalization
H(5) CC & retailer Collude	retailer	CC retailer: captain products no double marginalization (DM), non-captains: DM RCM retailer: all products have double marginalization

Notes: This table summarizes the key features of the null model (Captain Pricing Model) and alternative models. CC stands for captained, RCM stands for retailer category management.

Instrumental Variables (IVs): The conduct tests are based on sample analogues of the GMM moments defined in Equation 24. The existence of strong and valid instruments is crucial for testing firm conduct. The instruments should satisfy the following requirements:

First, validity requires that instruments should be exogenous to the unobserved marginal costs under the true model. The literature provides two sets of candicate IVs: BLP IVs such as sum of characteristics of other products produced by the same firm, or by rivals; Differentiation IVs such as number of closeby rivals and difference in product characteristics with closeby rivals (Berry and Haile 2014, Gandhi and Houde 2019).

Second, relevance requires that the instruments should predict or correlate with margins under different models. In the testing setting, strong instruments should be able to predict retail and wholesale margins for both candidate models. For example, consider double markups model and captain pricing model. Double markups model explains the price difference between the captain products and non-captain products by predicting higher margins and lower residual marginal costs for the captain (due to captain's shelf advantage); whereas the captain pricing model rationalizes the price difference by predicting lower margins for the captain (due to the contract), and not necessarily lower residual marginal costs. Therefore, the two models have different predictions in the distributions of markups and residual marginal costs. If double markups model is wrong, and if the instruments are strong in predicting higher markups for the captain, then the test is able to reject the double markups model.

Intuitively, relevance requires that the construction of IVs captures the nature of pricing behaviors and its implications on substitution patterns. For instance, if it is assumed that the retailer sets the retail prices and all the products have double markups, then upstream firm ownership is important in predicting wholesale margins. Whereas if it is the captain who sets the retail prices and the captain eliminates double marginalization from its own products, then the markup shifters should reflect whether product j belongs to a captain brand or not, in order to create an asymmetric effect on margins between captain's products and non-captain's products.

In the conduct tests, I use two groups of instruments (Table 20). (1) BLP IV: sum of characteristic differences of other products belonging to the same brand (or different brands), which use firm ownership to shift all products' margins; (2) BLP IV $\times$ captain identity: sum of characteristic differences of the same brand (or different brands) interacted with an indicator for captain's products, which predicts the captain's margins. For a product-retailer-market jrm (omitting time subscript), let O_{jrm} be the set of products other than j by the same firm that are sold in the retailer-market (rm), R_{jrm} be the set of products produced by rival firms that are sold in the retailer-market. Let x_{jrm} denote the product characteristics of product j in the retailer-market.

Table 20: Definition of the Instrumental Variables Used in the Conduct Tests

Instrumental Variables	Definitions	Number of IVs
BLP IV	$\sum_{j' \in O_{jrm}} x_{j'rm}$; $\sum_{j' \in R_{jrm}} x_{j'rm}$	2
BLP IV $\times$ captain identity	$1(\text{j is CC}) * x_{jrm} \sum_{j' \in O_{jrm}} (x_{j'rm} - x_{jrm})$; $1(\text{j is CC}) * x_{jrm} \sum_{j' \in R_{jrm}} (x_{j'rm} - x_{jrm})$	3

5.2 Conduct Test Results

In this session I discuss the results from the conduct tests. First I show test results on all the retailers; then results for the subset of retailers with a captain; finally I discuss results from the subset of RCM retailers. For each test, two sets of results are produced: one is based on the deterministic classification results, the other one is based on the results from Gibbs sampler. Since the preferred classification method is Gibbs sampler, I present in this section the results using classification from Gibbs sampler. The test results with deterministic classification are qualitatively the same and presented in Appendix G.

In all the tests, I orthogonalize prices, margins,and instrumental variables with respect to cost variables (including milk price × fat, sugar price × sugar, plastic price × size, diesel price × distance, diesel price × size, and distance × size), as well as retailer, brand, year fixed effects, and captain brand × retailer fixed effects, to control for unobserved characteristics that can be correlated with the residual marginal costs.

Test on All Retailers. I first conduct tests on the full sample with all the retailers, incorporating the 10,000 assignment matrices. Table 21 presents the test statistics for pairwise comparisons between the null model (captain pricing model) and all the alternative models. The column is the null model, which is tested against the alternative models on the row. When the test statistic is negative and below the critical value chosen (-1.96 for a 2.5% significant level), I reject the hypothesis in the row in favor of the hypothesis in the column. When the test statistic is between the two critical values $(-1.96, 1.96)$, it means that the hypotheses can not be statistically distinguished from each other. When the test statistic is positive and above the critcal value (1.96 for a 2.5% significant level), I reject the alternative models in the column in favor of the ones in the row. From the pairwise comparisons, the captain pricing model rejects alternatives H(2) to H(5), which means that the captain pricing model provides the most reasonable fit given the other specified alternatives from H(2) to H(5). The captain pricing model is statistically indeterministic from the captain & retailer collude model (H(6)). The two models have in common that the captain products do not have double marginalization and the non-captain products have double margins, but differ in who sets retail prices (the captain sets prices in the captain pricing model, while the retailer sets retail prices in the collusion model). Overall, the test results from Table 21 are consistent with the prediction from the stylized supply model that the captain eliminates double marginalization from its own products, but its rivals still have double markups.

Table 21: Rivers-Vuong Test Results for All Retailers

	Alternative models				
	H(1)	H(2)	H(3)	H(4)	H(5)
Null model	Double Markups	Zero Wholesale Markups	Zero Retail Markups	DN YP no DM	CC retailer Collude
H(0) Captain Pricing	-2.64 (0.01)	-3.37 (0.00)	-6.26 (0.00)	-3.16 (0.00)	1.88 (0.06)

Notes: This table reports test statistics from Rivers-Vuong test for all the retailers in the sample. The null model H(1) is in the column, and tested against the alternative models in the row. When calculating the statistics, I orthogonalize prices, margins, and instruments with respect to the cost shifters, brand, year, retailer, and captain brand × retailer fixed effects.
CC Pricing: captain has no double markups, non-captains have double markups, captain chooses prices; All with DM: all products have double markups, the retailer chooses prices; All zero WPCM: all products have zero wholesale margin, the retailer chooses prices; All zero RPCM: all products have zero retail margin, the retailer chooses prices; DN & YP no DM: neither Dannon nor Yoplait have double markups, the captain chooses prices; CC retailer Collude: captain does not have double markups, non-captains have double markups, retailer chooses prices.

Test on Retailers with a Captain. Next I conduct the tests on the subset of retailers classified to have a captaincy arrangement. Test statistics are reported in Table 22. The null model in the column is compared with the alternative models in the row. In addition to H(2) through H(6), I also test another hypothesis (H(7)), where the captain brand identity is flipped. The results show that in the group of retailers with a captaincy arrangement, the model that provides the most reasonable fit is the captain pricing model: the captain makes retail pricing decisions for all the products, eliminating double marginalization from its own products, and imposing double marginalization on its rivals' products.

Note that across all the tests shown in Table 21 and Table 22, the model where captain and retailer collude escapes rejection against the captain pricing model. From a joint profit maximization point of view, it is likely that the total profit is higher when pricing decisions are left to the retailer who takes into account substitution patterns among all the products. In turn, the captain will be able to reap a higher profit by revenue sharing mechanism, while also benefiting from elimination of double marginalization.

Table 22: Rivers-Vuong Test Results for Retailers with a Captain

	Alternative models					
	H(1)	H(2)	H(3)	H(4)	H(5)	H(6)
Null model	Double Markups	Zero Wholesale Markups	Zero Retail Markups	DN YP no DM	CC retailer Collude	Opposite CC
H(0) Captain Pricing	-2.32 (0.02)	-3.15 (0.00)	-5.16 (0.00)	-2.46 (0.01)	2.02 (0.04)	-3.45 (0.00)

Notes: This table reports Rivers-Vuong Test statistic on retailers with a captain. When calculating the statistics, I orthogonalize prices, margins, and instruments with respect to cost shifters, brand, year, retailer, and captain brand × retailer fixed effects.
CC Pricing: captain has no double markups, non-captains have double markups, captain chooses prices; All with DM: all products have double markups, the retailer chooses prices; All zero WPCM: all products have zero wholesale margin, the retailer chooses prices; All zero RPCM: all products have zero retail margin, the retailer chooses prices; DN & YP no DM: neither Dannon nor Yoplait have double markups, the captain chooses prices; CC retailer Collude: captain does not have double markups, non-captains have double markups, retailer chooses prices. Opposite CC: captain identity is flipped.

Test on RCM Retailers. Lastly, I conduct the tests on the subset of retailers classified into RCM. For this set of retailers with no captaincy arrangement, I specify H(2) (all products have double marginalization, retailer makes retail pricing decisions) as the null model. The alternative models include: Dannon is the captain, Yoplait is the captain, zero wholesale margin, zero retail margin, no double markups for Dannon or Yoplait, and captain and retailer collude. Table 23 shows the test results. The null model is mostly indistinguishable from the alternative models, and is rejected by H(3) and H(4). These results indicate that the RCM retailers do not have the traditional problem of double marginalization resulting from the simple linear pricing model. Specifically, the test results of H(2) against H(1) DN-CC and H(1) YP-CC, along with the empirical evidence on the lack of asymmetries in share and unobserved quality of product placement, suggests that these retailers do not seem to have favoritism arrangements with Dannon or Yoplait. Moreover, the test result against H(3) suggests that these retailers have better capacity to negotiate good terms of contract with wholesalers compared to the retailers using captaincy arrangements. Incorporating the facts that the RCM retailers sell more store brands, and are bigger in store size and geographic coverage (Appendix F), a plausible explanation for the findings in Table 23 is that the RCM retailers are in general more efficient in shelf management and more sophisticated in negotiating with manufacturers. For example, they may use the larger presence of store brands as leverage in negotiations with the upstream firms.

Table 23: Rivers-Vuong Test Results for Retailers without Captaincy Arrangement

	Alternative models					
	H(0)	H(0)	H(2)	H(3)	H(4)	H(5)
Null model	Dannon Captain	Yoplait Captain	Zero Wholesale Markups	Zero Retail Markups	DN YP no DM	CC Retailer Collude
H(1) Double Markups	1.46 (0.14)	0.19 (0.85)	3.20 (0.00)	2.18 (0.02)	-0.02 (0.98)	-1.58 (0.11)

Notes: This table reports Rivers-Vuong Test statistic on retailers without captaincy arrangement (RCM retailers). When calculating the statistics, I orthogonalize prices, margins, and instruments with respect to cost shifters, brand, year, retailer, and captain brand × retailer fixed effects.
All DM: all products have double markups, the retailer chooses prices; DN CC: Dannon has no double markups and chooses prices, non-captains have double markups; YP CC: Yoplait has not double markups and chooses prices, non-captains have double markups; All zero WPCM: all products have zero wholesale margin, the retailer chooses prices; All zero RPCM: all products have zero retail margin, the retailer chooses prices; DN & YP no DM: neither Dannon nor Yoplait have double markups, the captain chooses prices; CC retailer Collude: captain does not have double markups, retailer chooses prices.

Discussion. I end this session with a brief discussion about other possible vertical contracts. Another vertical contract commonly used in retail grocery industry is slotting allowances, which include manufacturers' upfront payments that are independent of the retailers' subsequent quantity purchases, to buy up scarce shelf space in order to exclude their smaller rivals from the market (Marx and Shaffer 2010, Hristakeva 2019, 2020). According to industry practice, captaincy and slotting allowances are not mutually exclusive. Some retailers base new product selections solely on the captain's category plan but charge slotting allowances to offset the cost of stocking the new product. Other retailers weigh both captain's category plan and slotting allowances when deciding which new products to offer. The underlying incentive of retailers is similar: the retailers can leverage shelf space scarcity to extract rents from the manufacturers, either in the form of slotting allowances, or a fixed payment for the captaincy position. Slotting allowance can explain the market share or assortment asymmetries, however, it is less likely to explain the asymmetry in markups between the leading brand and the other brands.[33] Hristakeva (2019) shows that the re-

[33] In fact, theory papers do not have a consensus on the effect of slotting allowance on retail price. In Marx and Shaffer (2010), slotting allowances do not affect consumer prices. In Sullivan (1997), slotting allowances may lower retail prices because they are an efficient mechanism for the retailer to equate the supply and demand of shelf space. In Shaffer (1991), slotting allowances may raise consumer prices because without them retailers would use their bargaining powers to negotiate lower wholesale price.

placement threat from slotting allowances puts a downward pressure on wholesale price, but it does not eliminate double markups. Vertical contracts may include other incentives such as quantity discounts, discounts that lower the retailer's wholesale price on every unit purchased when the retailer's purchase exceed some quantity threshold (Kolay et al. 2004, Conlon and Mortimer 2013). These are partly captured in the pricing models because they are paid per unit-sold.[34] Furthermore, quantity discounts do not guarantee elimination of double markups either.[35]

In some other industries such as automobile, television, movies, and video rental, there exist other types of vertical contracts exist that can also reduce or eliminate double marginalization and achieve efficiency in the supply chains. For example, quantity forcing, franchise fee, or full-line forcing (Mathewson and Winter 1984, Ghosh and Salant 2008, Salant et al. 2016, Ho et al. 2012, Genchev and Mortimer 2016). Quantity forcing and franchise fee can achieve supply chain efficiency through similar mechanism as the captaincy contract: for example, in automobile franchising, wholesalers sell to dealers at marginal cost, and collect rents through franchise fees. But a unique feature in grocery retail industry is product placement and shelf space allocation — the beachfront property at the store is so valuable that the manufacturers are fighting for every inch of it. The two inference tests, combined together, point to the type of vertical contract (captaincy arrangement) that best explains the entire set of stylized facts about asymmetries in prices, market shares, product assortments and quality of product placement in the yogurt category.

6 Counterfactual Analysis

The two inference test results suggest that category captaincy arrangement is associated with asymmetries in two dimensions: quality of product placement and markups across products. This can affect competition among products, generate efficiency gain/loss for retailers and manufacturers, and affect consumer welfare. I investigate these effects of captaincy using the group of retailers identified as having captaincy arrangement by the classification. In the counterfactuals, I change captain pricing (referred to as *price effect*), or quality of product placement (referred to as *placement effect*), or product choice-set (referred to as *assortment effect*) in these retailers, and evaluate the changes in market outcomes, including market share, price, profit and consumer welfare.

[34] "Partly" because the pricing equations include captain brand $\times$ retailer dummies. I am working on including brand $\times$ retailer dummies to control for differences in retailer marginal costs due to contracts like quantity discounts.

[35] For instance, Conlon and Mortimer (2013) studies an all-unit discount contract used by a dominant chocolate candy manufacturer in the US (Mars, Inc). The contract consists of three main features: a per-unit discount, a quantity target, and a 'facing' requirement that the retailer carry at least six Mars products.

An important input in the counterfactual analyses is the estimated quality of product placement captured by the demand structural shock term $\hat{\xi}_{jrmt}$. To make valid comparisons across retailer-markets, and to reduce noises in this estimated structural term, I implement the following procedure to generate for each retailer a baseline quality of product placement $\hat{\xi}^{0}_{jrmt}$ that reflects favoritism toward captain products, and a counterfactual quality of product placement $\hat{\xi}^{cf}_{jrmt}$ from which the higher quality of product placement for the captain products is removed:

Take a Dannon-captained retailer,

(1) Generate baseline $\hat{\xi}^{0}_{jrmt}$ using predicted brand-retailer fixed effect $\hat{\gamma}_{br}$, product fixed effect $\hat{\gamma}_j$, market fixed effect $\hat{\gamma}_m$, and year fixed effect $\hat{\gamma}_t$ from Equation 26, estimated from all the *DN-CC* retailers.

$$\hat{\xi}_{jrmt} = \gamma_{br} + \gamma_j + \gamma_m + \gamma_t + \epsilon_{jrmt} \tag{26}$$

(2) Generate counterfactual $\hat{\xi}^{cf}_{jrmt}$ predicted brand-retailer fixed effect $\hat{\gamma}_{br}$, product fixed effect $\hat{\gamma}_j$, market fixed effect $\hat{\gamma}_m$, and year fixed effect $\hat{\gamma}_t$ from Equation 26, estimated from all the *Non-CC* retailers.

Now I use $\hat{\xi}^{0}_{jrmt}$ and $\hat{\xi}^{cf}_{jrmt}$ to conduct counterfactual analyses. I compare counterfactual outcomes to baseline estimates obtained using $\hat{\xi}^{0}_{jrmt}$ and captain pricing model. Besides market share and price, the other market outcomes that I evaluate include profit, consumer welfare, and markup. The definitions are listed as follows:

(1) Joint profit of the captain and retailer (Equation 27).

$$\sum_{j \in J_r^{cc}} (p_j - c_j) \sum_{\forall m: j \in m} s_{jm} + \sum_{j \in J_r^{nc}} (p_j - w_j) \sum_{\forall m: j \in m} s_{jm} \tag{27}$$

(2) Vertical supply chain profit (Equation 28).

$$\sum_{j \in J_r^{cc}} (p_j - c_j) \sum_{\forall m: j \in m} s_{jm} + \sum_{j \in J_r^{nc}} (p_j - c_j) \sum_{\forall m: j \in m} s_{jm} \tag{28}$$

(3) Total profit from the non-captain (Equation 29). Note that this is not the profit that the non-captain products get. It provides a baseline comparison to the total supply chain profit.

$$\sum_{j \in J_r^{nc}} (p_j - c_j) \sum_{\forall m: j \in m} s_{jm} \tag{29}$$

(4) Consumer welfare change in percentage (Equation 30, omitting subscripts for retailer, market and year). NS is the total number of households in the retailer-market in the demand model (1000 for each retailer-market), α_i is consumer marginal utility of income estimated from the demand model.

$$\Delta(\text{CS})' = \frac{\left[\frac{1}{NS}\sum_{i=1}^{NS}\frac{1}{\alpha_i}\left(\ln\sum_{j=0}^{J} exp(X_j'\beta + \xi_j')\right) - \frac{1}{NS}\sum_{i=1}^{NS}\frac{1}{\alpha_i}\left(\ln\sum_{j=0}^{J} exp(X_j\beta + \xi_j)\right)\right]}{\frac{1}{NS}\sum_{i=1}^{NS}\frac{1}{\alpha_i}\left(\ln\sum_{j=0}^{J} exp(X_j\beta + \xi_j)\right)} \tag{30}$$

I first illustrate the effects of category captaincy using one Dannon-captained retailer in one market as an example. Counterfactual one evaluates the effects of the captain pricing (*price effect*), and counterfactual two evaluates the effects of the quality of product placement (*placement effect*). The results on share, price and consumer welfare from counterfactual one and two are presented in Table 24, and the results on markup and profits from counterfactual one and two are presented in Table 25. Counterfactual three evaluates the effects of product choice set (*assortment effect*), the results from which are reported in Table 27 and Table 28. In all four tables, the first column (column (1)) is the baseline market outcomes calculated using the asymmetric ξ^0_{jrmt} and captain pricing model. I then scale up the analysis to include all the Dannon-captained retailers in 2016.

Counterfactual 1: Impacts of Eliminating Double Marginalization from Captain Products. To evaluate the effects of captain pricing (elimination of double marginalization of the captain's products) on market outcomes, I change the captain pricing model to double marginalization model in this Dannon-captained retailer, while keeping the quality of product placement (the baseline $\hat{\xi}^0_{jrmt}$) fixed. Thus, in this counterfactual scenario, the captain products still enjoy a higher quality of product placement on the shelves, but are priced with double margins as all the other products. Different from the baseline captain pricing model where the captain sets retail prices, in this counterfactual the retailer sets retail prices.

Column (2) in Table 24 shows the shares, prices and consumer welfare change from this counterfactual analysis. Imposing double marginalization on the captain's products increases their prices by 19.28%, and shrinks their market shares by 53.91%. All of the reduction of captain's market share is diverted to the non-captain brands, and the non-captain products' prices reduce by 1.43%. These results suggest anti-competitive effects resulting from elimination of double-marginalization of the captain's products.

Consumer welfare decreases by around 7.83% in this counterfactual due to the increase of the category average price, which suggests that eliminating double marginalization from the captain's products leads to consumer welfare gain.

Turning to profit and markup changes in Table 25 (Column (2)), the joint profit of the captain and retailer decreases by 10.11% compared to the baseline, which is mostly due to the changes in the captain's prices and shares. This implies that the retailer has efficiency gain from eliminating double markup from the captain's products. The total vertical chain profit increases by 5.34%, which is mainly driven by the non-captain products making more profit under the counterfactual scenario. This is reflected in the increase of the non-captains' wholesale markups.

Counterfactual 2: Impacts of Quality of Product Placement. In the second counterfactual, I remove the higher quality of product placement that the captain's products receive, by replacing the baseline $\hat{\xi}^{0}_{jrmt}$ with $\hat{\xi}^{cf}_{jrmt}$ which is the average quality of product placement from the non-captained retailers. I then simulated counterfactual market outcomes based on the captain pricing model, allowing the captain to set prices.

Column (3) in Table 24 shows results on prices, shares and consumer welfare for this counterfactual. I find that the captain brand's market share evaporates by around 44.37%, and its price decreases by 2.26% in response to the decrease in the quality of product placement. All of the captain's share reduction is diverted to the non-captain products, whose prices also see an increase of 0.36%. Interestingly, consumer welfare increases by 8.40% with the elimination of asymmetry in product placement, which suggests that the consumers in this retailer incur welfare losses from the category captaincy due to reduced variety and less presence of the non-captain products.

Turning to profit and markup changes in Table 25 (Column (3)), the vertical profit from the non-captain brands increases by about 12.90%. However, the joint profit of the captain and retailer decreases by 11.17%, and the vertical supply chain profit also decreases by 2.16%, largely driven by the worsened brand performance of the captain. The average markup of the non-captain products increases by about 1.73%, while the markup of the captain decreases by 2.79%.

From the results presented so far, I find that the consumer welfare under category captaincy changes in the opposite direction in counterfactual one and two: eliminating double markups on the captain generates consumer welfare gain, while overly favoring the captain brand on the shelves leads to consumer welfare loss. Therefore, the combined effect from category captaincy on consumer welfare, will depend on the relative magnitude between the price effect and the placement effect, and will likely vary across retailers. In column (4) of Table 24 I completely eliminate both the pricing and the product placement advantage of the captain. The consumer welfare decreases by 9.13%, which means that in this retailer, the price effect dominates the placement effect.

Table 24: Results from Counterfactual One and Counterfactual Two —Share, Price and Consumer Welfare

	(1)	(2)	(3)	(4)
	Baseline	Price Effect	Placement Effect	Price & Placement Effect
Share				
Dannon (captain)	0.343	0.158	0.191	0.078
non-captain	0.564	0.719	0.639	0.725
Yoplait	0.094	0.124	0.171	0.198
Outside Share				
	0.622	0.583	0.583	0.583
Price				
Dannon (captain)	1.269	1.514	1.241	1.495
non-captain	1.684	1.660	1.690	1.678
Yoplait	0.857	0.834	0.854	0.843
Category Average	1.574	1.615	1.552	1.604
Consumer Welfare Change (%)				
		-7.828	8.399	-9.126

Notes: This table shows share, price, and consumer welfare change from counterfactual 1 and 2, using one representative retailer. Brand share is brand-retailer-market share conditional on purchase. Brand price is sales averaged price. I calculate the mean for the non-captain products' outcomes.

Table 25: Results from Counterfactual One and Counterfactual Two —Profit and Markup

	(1)	(2)	(3)	(4)
	Baseline	Price Effect	Placement Effect	Placement & Price Effect
Markup				
non-captain: wholesale	0.173	0.177	0.176	0.178
non-captain: retail	0.301	0.289	0.292	0.286
Dannon: wholesale		0.188		0.188
Dannon: retail	0.394	0.306	0.383	0.302
Profit				
Captain + Retailer	0.188	0.169	0.167	0.156
Total Chain	0.264	0.278	0.258	0.262
non-captain	0.016	0.020	0.018	0.019

Notes: This table shows profit and markup from counterfactual 1 and 2, using one representative retailer. I calculate the mean for the non-captain products' outcomes.

Counterfactual 3: Impacts of Choice Set Distortion. In this counterfactual, I quantify the potential effects from the captain distorting the choice set in favor of its own products. I reconfigure the choice set of the Dannon-captained retailer using product choice sets of two of the RCM retailers in the same market, keeping the total number of products fixed (Table 26 shows the product choice set change in the counterfactual).

Table 26: Product Choice Set Change in Counterfactual Three

Number of Products	Dannon-Captained Retailer	RCM Retailer	Counterfactual Retailer
Dannon	20	10	8
Yoplait	7	9	9
Other	61	52	65
All	82	71	82

Notes: This table shows the product choice set in the Dannon-captained retailer, another RCM retailer in the same market that is used to replace the choice set of the Dannon-captained retailer, and the counterfactual product set. The counterfactual choice set is used in counterfactual 3.

Using the counterfactual product choice set, as well as the counterfactual $\hat{\xi}^{cf}_{jrmt}$, I simulate the equilibrium market outcomes for this Dannon-captained retailer using the captain pricing model. Table 27 (Column (2)) reports the counterfactual shares, prices, and consumer welfare changes. Despite a 18.92% decrease in price, the captain's market share decreases by 37.32%. This is caused by two changes: the captain's quality of product placement is reduced, and its number of products decreases by more than a half. The change in choice set leads to an increase in consumer welfare by around 45.63%. It also leads to a 10.64% increase in the profit of the alliance between the retailer and the captain (Table 28).

Table 27: Results from Counterfactual Three — Share, Price and Consumer Welfare

	(1)	(2)
	Baseline	Assortment Effect
Share		
Dannon (captain)	0.343	0.079
non-captain	0.564	0.778
Yoplait	0.094	0.143
Outside Share		
	0.623	0.562
Price		
Dannon (captain)	1.269	1.294
non-captain	1.683	1.633
Yoplait	0.857	0.876
Category Average	1.573	1.595
Consumer Welfare Change (%)		
		10.308

Notes: This table shows share, price and consumer welfare change from counterfactual 3, using one representative retailer. Brand share is brand-retailer-market share conditional on purchase. Brand price is sales averaged price. I calculate the mean for the non-captain products' outcomes.

Table 28: Results from Counterfactual Three —Profit and Markup

	(1)	(2)
	Baseline	Assortment Effect
Markup		
non-captain: wholesale	0.173	0.182
non-captain: retail	0.301	0.328
Dannon (captain)	0.394	0.442
Profit		
Captain + Retailer	0.188	0.218
Total Chain	0.264	0.333
non-captain	0.016	0.022

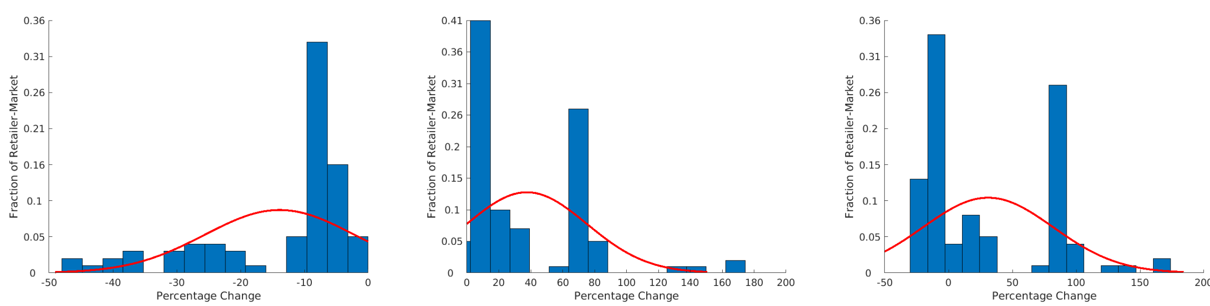
Notes: This table shows profit and markup from counterfactual 3, using one representative retailer. I calculate the mean for the non-captain products' outcomes.

Scale up to All the Dannon-Captained Retailers Scaling up to all the Dannon-captained in 2016, I reproduce the counterfactual one and two analyses. The main conclusions from the one retailer example remain. Category captaincy creates anti-competitive effects through pricing and product placement: removing the pricing advantage of the captain reduces its share by 51.28%, and removing the product placement advantage of the captain decreases its share by 35.87%. All of the share reduction is diverted to the non-captain products. At the same time, category captaincy generates efficiency gain for the alliance between the captain and the retailer: on average, removing the pricing advantage from the captain results in a 10.22% decrease in the alliance profit, whereas removing the product placement advantage from the captain leads to a 11.27% decrease in the alliance profit.

As we have seen from counterfactual one and two, the combined effect of category captaincy on consumer welfare can be either positive or negative, depending on the relative magnitude between the price effect and the placement effect. Figure 7 illustrates this heterogeneous trade-off across retailers. Panel (a) shows that imposing double markups on the captain's products (conditional on the quality of product placement) always leads to reductions in consumer welfare, due to higher category prices. Panel (b) shows positive consumer welfare changes from eliminating product placement advantage of the captain. The magnitude of the consumer welfare changes depends on differences in consumer preferences and heterogeneity in demographic compositions across retailers. The combined effects from eliminating pricing and product placement advantage of the captain on consumer welfare, can be either positive or negative as shown in Panel (c).

Figure 7: Consumer Welfare Change (%) in Dannon-Captained Retailers

(a) Price Effect | (b) Placement Effect | (c) Placement & Price Effect

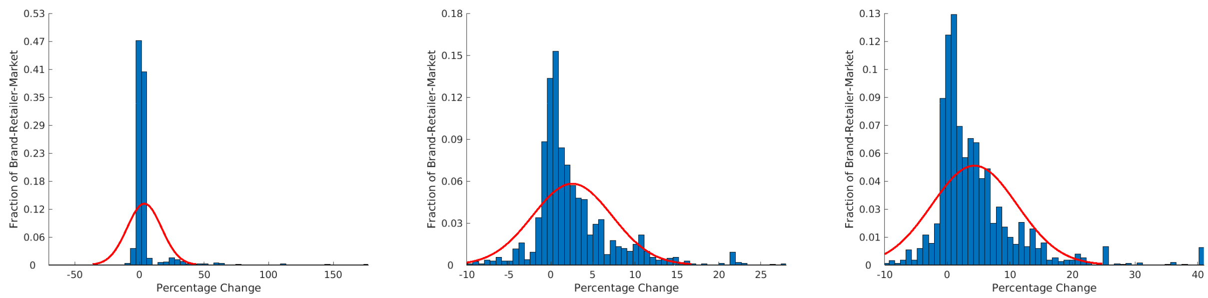


Notes: This figure depicts the consumer welfare changes in counterfactual one and two, for all the Dannon-captained retailers in 2016. The consumer welfare change is calculated for each retailer-market.

Figure 8 depicts the effects of category captaincy on the non-captain brands' wholesale markups. In general, removing the captain's advantage in pricing and/or product placement will increase the non-captain brands' market power. Imposing double marginalization on the captain brand leads to an average 3.14% increase in non-captains' wholesale markup (Panel (a)). Neutralizing the quality of product placement generates on average a 4.96% increase in wholesale markup for the non-captain brands (Panel (b)). These results suggest anti-competitive effects of category captaincy arrangement on rival brands.

Figure 8: Non-captain Wholesale Markup Change (%) in Dannon-Captained Retailers

(a) Price Effect (b) Placement Effect (c) Placement & Price Effect



Notes: This figure depicts the non-captain wholesale markup changes in counterfactual one and two, for all the Dannon-captained retailers in 2016. The wholesale markup change is calculated for each brand-retailer-market. I winsorize the wholesale markup changes at 1% level.

Bounds on Profit Share (Preliminary). Counterfactual one and two suggest that category captaincy generates efficiency gain to the alliance between the retailer and the captain, through both pricing and product placement effects. Without estimating the profit split between the captain and the retailer, which is out of the scope of this paper, one can not determine with certainty that the retailer's profit will increase with elimination of double markups from the captain's products, or with favorable product placement given to the captain. However, under simplifying assumptions, I can derive coarse bounds on the profit share that the captain keeps for itself (ϕ^{cc}), such that both the captain and the retailer are better off with captaincy arrangement than without.

For simplicity, I make the following assumptions: (1) category management costs, both of the category captain and the retailer, are equal to zero; (2) the two brands are symmetric.[36] Under these assumptions, the equilibrium conditions (6) and (7) derived in subsection 3.4 for ϕ^{cc} can be simplified into inequalities (31): conditional on the quality of product placement, the first inequality ensures that the retailer's profit under captaincy is not less than that under RCM; and the second inequality ensures that the profit that the captain keeps for itself under captaincy is not less than the counterfactual profit it gets under RCM (consistent with the stylized captaincy model, I use subscript 1 to denote the captain brand and subscript 2

[36]The category management costs can be estimated from the FOCs of ξ_{brt}, but it is not the focus of this paper. I maintain the assumption that the two brands are symmetric so that the offer from the other brand does not need to be taken into account in the equilibrium conditions for ϕ^{cc}. If one were to take into account the rival brand's offer to the retailer, the bounds would be shifted closer to zero.

to denote the non-captain brand). The definitions and values of the counterfactual profits are presented in Table 29, where the values are simulated profits from the Dannon-captained retailer example.

$$\begin{cases} (1-\phi^{cc})\Pi_A^{cc=1} \geq \Pi_r^{rcm} \\ \phi^{cc}\Pi_A^{cc=1} \geq \Pi_1^{rcm} \end{cases} \tag{31}$$

Table 29: Definition and Value of the Equilibrium Profits in Equation 31

Equilibrium Profits	Definition	Value
$\Pi_A^{cc=1} = (p-c)s_1^{cc} + (p-w)s_2^{cc}$	captain+retailer profit under captaincy	0.1888
$\Pi_r^{rcm} = (p-w)s^{rcm}$	retailer profit under RCM	0.1694
$\Pi_1^{rcm} = (w-c)s_1^{rcm}$	captain profit under RCM	0.0067

I can solve for the range of ϕ^{cc} according to the inequalities $\frac{\Pi_1^{rcm}}{\Pi_A^{cc}} \leq \phi^{cc} \leq 1 - \frac{\Pi_r^{rcm}}{\Pi_A^{cc}}$, which implies a bound on the equilibrium profit share: $0.035 \leq \phi^{cc} \leq 0.1$. This is the range of profit share that the captain keeps for itself which is compatible with both the captain and the retailer's incentive constraints, such that both of them benefit from the efficiency gain of eliminating double markups of the captain's products.

7 Discussions and Implications

The retail industry has employed category captaincy for two decades. However, due to data limitations especially the unavailability of captaincy arrangement, little empirical work has been done so far to study its consequences. Using retail price and quantity data, I apply empirical strategies to infer the existence and prevalence of this vertical practice, and quantify its impacts on retail industry. The inference approaches, which match the stylized empirical evidence, industry knowledge, and theoretical predictions, are based on (i) model estimated quality of product placement that a brand enjoys within a retailer; (ii) theory about captain pricing strategy.

First, I document stylized empirical evidence that is consistent with the existence and implication of category captaincy. The category captaincy arrangement seems to create significant asymmetry in market shares between the top two brands in yogurt category across retailers. I hypothesize that this asymmetry in shares is partly caused by differences in the quality of product placement across products, such as eye-level placement, end-of-aisle display, or increased number of facings, most of which are unobserved from the data. I then estimate a demand model to isolate the unobserved quality of product placement from observable demand factors and consumer tastes. The estimated brand-retailer fixed effect from the model explains most of the unexplained market share variation, and exhibits similar asymmetric patterns between brands across retailers as in the market share. I then estimate a finite mixture model to classify retailers into different types of captaincy arrangement, using the estimated brand-retailer fixed effect as a proxy for the quality of product placement, as well as fraction of UPCs calculated from the data. This inference approach abstracts from specific forms of unobserved favoritism arrangements.

Second, I hypothesize that the asymmetry in shares can also be driven by asymmetry in pricing and margins. The partnership between the captain brand and the retailer allows the captain to take advantage of vertically-integrated pricing strategy and eliminate double marginalization from its own products. This hypothesis implies a captain pricing model for the retailers classified as captain retailers, and a double marginalization model for retailers classified as RCM. Conditional on the classification results, a series of conduct tests support my theory model predictions that the captain eliminates double marginalization from its own products in retailers where it has control over the shelves, while the non captain products still have double markups. The supply model and the conduct tests provide novel insights into the price-setting behaviors of the category captains. The captain pricing can affect efficiency and competition patterns within a given retailer. Pricing under captaincy arrangement has not been empirically examined, as the literature on vertical relationships has not considered cases where significant heterogeneity in vertical contracts exists across retailers, which should be taken into account given the empirical evidence presented in this paper.

Lastly, the counterfactual analyses examine several possible channels through which the category captain can affect non-captain brands' performance and the supply-chain profits. These channels include quality of product placement, which can directly boost sales of the captain's products; lower prices for captain products; and potential choice-set distortions that affect consumer choices and reduce competition. Category captaincy arrangements increase market shares of the captain by about 50%, but they can also increase retailer profits and consumer welfare by eliminating double markups on the captain's products.

My findings offer useful insights for policy makers and industry practitioners.

Implications for Policy My paper provides a series of empirical methods to make inference about the existence and prevalence of category captaincy arrangement. The controversial role of category captaincy has triggered multiple investigations into the practice and its consequences, but the biggest hurdle is that these arrangements are secretive. My work presents the first step toward analyzing the benefits and harms of category captaincy arrangement, without observing the real arrangements. I show data evidence as well as model estimates that indicate that the captaincy practice is relatively prevalent. My counterfactual analyses quantify potential anti-competitive and efficiency-enhancing effects of category captaincy, and highlight the important role of the retailer in policing category captaincy.

Implications for Practice Turning to the managerial implications of my work, category captaincy is a potentially winning strategy for the captain brand. The firm appointed as the captain will benefit significantly from a higher quality of product placement such as better shelf placement, more promotions and display, as well as lower price levels resulting from vertically-integrated pricing. On the other hand, the non-captain brands face fiercer competition on the shelf and in prices, therefore, they suffer revenue losses. For retailers, there can be an efficiency gain from elimination of double marginalization from the captain's products. Thus, if a retailer is not sophisticated enough (or does not have enough bargaining power) to negotiate favorable vertical contract with all the manufacturers, developing an integrated pricing strategy with the leading brand is a good alternative. Moreover, the retailer can tap into the captain's shelf management resources and save management costs. However, my counterfactual results imply a caveat to the practice of captaincy—excessive favoritism to the captain brand in the shelf space can reduce consumer welfare.

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Appendices

A Data Appendix

Table A1 summarizes the sources of cost data and the variables used in the demand model.

Table A1: Cost Data and Sources

Cost	Note	Source
Milk Price	Whole milk, reduced milk and skim milk: retail price at MSA level	USDA Retail Milk Prices Report https://www.ams.usda.gov/sites/default/files/media/RetailMilkPrices2018.pdf
Plastic Price	Plastics Packaging Film and Sheet Manufacturing: Polypropylene/Polypropylene PPI at national level	U.S. Bureau of Labor Statistics, PPI https://www.bls.gov/ppi/ppidr201612.pdf
Sugar Price	Yearly average sugar prices at national level	https://www.macrotrends.net/2537/sugar-prices-historical-chart-data
Diesel Price	Annual diesel price at MSA level	U.S Energy Information Administration: Retail Gasoline and Diesel Prices

Table A2: Market Share of Top Five National Brands

National Ranking	Brand	National Share (%)	Store Share (%)	DMA Share (%)	Store Coverage (%)
1.	Dannon	25	25.4 (8.6)	25.2 (7.1)	100
2.	Yoplait	24	25.2 (10.4)	25.4 (7.1)	100
3.	Chobani	16	14.4 (6.2)	16.7 (3.2)	100
4.	Fage	5.6	5.3 (3.9)	5.5 (2.3)	81.5
5.	Stonyfield	2.9	2.2 (2.5)	2.8 (2.1)	89.3
12.	Tillamook	1.7	1.5 (8)	6.2 (8.7)	23.6

Notes: This table summarizes the mean and standard deviation (in parenthesis) of market shares of top five national brands, as well as Tillamook, a brand that leads market shares of two retailers. Chobani leads one retailer's share; Tillamook leads two retailers' share. Tillamook's products are available in Protland, Spokane, and Seattle, and its production facility is in Tillamook, OR. The regional distribution of Tillamook explains its relatively big market share dispersion.

B More Descriptive Evidence

B.1 Assortment Differences

Table 3 in the main text shows 52 retailers (out of a total of 88 retailers in 2016) with significant market share asymmetry. For these 52 Dannon-Led/Yoplait-Led retailers, Table B1 summarizes shares, assortments and prices at the store level within each retailer. Fraction Dannon Store stands for the fraction of stores within a given retailer, with Dannon leading the store market share. Fraction Dannon UPC is defined as the number of Dannon UPCs sold in a particular store divided by the total number of Dannon UPCs. Price Difference is the average store-level price of a 6oz Dannon yogurt minus the average price of a 6oz Yoplait yogurt. Results show asymmetry between Dannon and Yoplait *at the store level* for Dannon-Led and Yoplait-Led retailers, but no asymmetry for Non-Led retailers.

Table B1: Store Level Assortment and Price Asymmetry

	mean	sd	p25	p50	p75
Dannon-Led Retailers					
Fraction Dannon Store	0.973	0.048	0.962	1	1
Fraction Yoplait Store	0.026	0.047	0	0	0.038
Fraction Dannon UPC	0.153	0.038	0.13	0.168	0.179
Fraction Yoplait UPC	0.12	0.023	0.104	0.111	0.137
Price Difference	0.181	0.112	0.105	0.137	0.229
Yoplait-Led Retailers					
Fraction Dannon Store	0.028	0.063	0	0	0.016
Fraction Yoplait Store	0.959	0.091	0.98	1	1
Fraction Dannon UPC	0.081	0.042	0.05	0.073	0.1
Fraction Yoplait UPC	0.115	0.043	0.09	0.112	0.138
Price Difference	0.32	0.112	0.244	0.306	0.373
Non-Led Retailers					
Fraction Dannon Store	0.437	0.342	0.111	0.421	0.703
Fraction Yoplait Store	0.432	0.325	0.126	0.409	0.698
Fraction Dannon UPC	0.099	0.035	0.079	0.099	0.122
Fraction Yoplait UPC	0.092	0.033	0.084	0.095	0.105
Price Difference	0.259	0.1	0.2	0.224	0.315

Notes: Price difference is the average price of a 6oz Dannon product minus the average price of a 6oz Yoplait product.

To see whether and by how much UPCs of these two brands are over- or under- displayed in Dannon-led or Yoplait-led retailers, I estimate the following linear probability model at UPC-store-year level on a sample that only includes Dannon and Yoplait products in Dannon-led and Yoplait-led retailers:

$$y_{ist} = \gamma_i + \beta_1 \gamma_{i\in b} \times \gamma_s^{r=type} + \gamma_t + \epsilon_{ist} \tag{32}$$

where y_{ist} is an indicator variable equal to one if a UPC i is sold in store s in year t. The interaction term $\gamma_{i\in b} \times \gamma_s^{r=type}$ is equal to one if the observation is a Dannon UPC (Yoplait

UPC) in a Dannon-led (Yoplait-led) retailer. γ_i, γ_t are UPC and year fixed effects. The parameter of interest is β_1: as shown in Table B2, β_1 is estimated to be negative for Dannon in a Yoplait-led retailer, suggesting that Dannon UPCs are on average carried less by Yoplait-led retailers compared to Dannon-led retailers. The same holds true for Yoplait UPCs in Dannon-led retailers. Thus, the product assortments of Dannon and Yoplait also exhibit asymmetry across retailers

Table B2: Assortment Asymmetry across Retailers

	Carry or not	Carry or not
Dannon#Dannon-led	0	0
	(0)	(0)
Dannon#Yoplait-led	-0.0586***	-0.0369***
	(0.000164)	(0.000332)
Yoplait#Dannon-led	-0.00307***	-0.0258***
	(0.000155)	(0.000332)
Yoplait#Yoplait-led	0	0
	(0)	(0)
Constant	0.937***	0.941***
	(7.22e-05)	(8.76e-05)
Observations	25,203,550	25,203,550
R-squared	0.006	0.016
market FE	no	yes

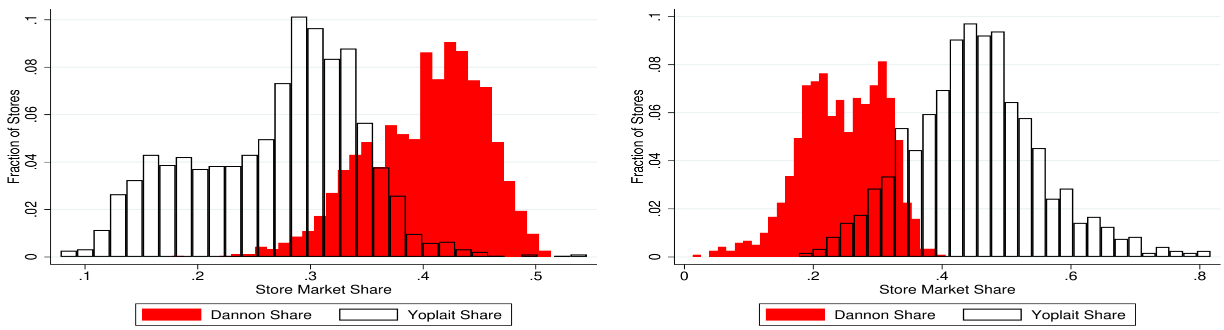
Notes: Linear probability model results estimated at UPC-store level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, standard errors in parentheses.

B.2 Retailers that Operate in Multiple Markets

In subsection 3.3, I identify 52 retailers at which the "leading brand" is either Dannon or Yoplait. 37 out of these 52 retailers operate in more than one market. Figure B1 visualizes the store market share distributions between Dannon and Yoplait for these multi-market retailers. The asymmetry in store market share between Dannon and Yoplait across these multi-market retailers is also very salient.

Figure B1: Store Share Distributions of Dannon-Led v.s. Yoplait-Led Multi-Market Retailers

(a) Dannon-led retailer **(b)** Yoplait-led retailer



Notes: Dannon-led and Yoplait-Led retailers are classified based on market share asymmetry as described in Table 3. A leading brand for a given retailer satisfies: (1) within chain-market share > national share for all markets; (2) the same across markets. Panel(a) depicts store market share of Dannon and Yoplait in Dannon-led retailers, Panel(b) depicts store market share of Dannon and Yoplait in Yoplait-led retailers.

Table B3 summarizes store shares, assortments and prices for retailers that span across multiple markets. The variables are defined in the same way as Table B1. The results again show asymmetry in assortment and price between Dannon and Yoplait for Dannon-Led and Yoplait-Led retaielrs spanning across multiple markets, but no asymmetry for non-led multi-market retailers.

Table B3: Store Level Assortment and Price Asymmetry Multi-Market Retailers

	mean	sd	p25	p50	p75
Dannon-Led Retailers					
Fraction Dannon Store	0.956	0.056	0.902	0.973	1
Fraction Yoplait Store	0.043	0.055	0	0.027	0.098
Fraction Dannon UPC	0.16	0.033	0.156	0.167	0.183
Fraction Yoplait UPC	0.125	0.025	0.104	0.132	0.139
Price Difference	0.166	0.093	0.101	0.131	0.229
Yoplait-Led Retailers					
Fraction Dannon Store	0.024	0.056	0	0	0.016
Fraction Yoplait Store	0.959	0.095	0.98	1	1
Fraction Dannon UPC	0.075	0.034	0.057	0.073	0.087
Fraction Yoplait UPC	0.111	0.042	0.086	0.11	0.135
Price Difference	0.331	0.115	0.244	0.328	0.379
Non-Led Retailers					
Fraction Dannon Store	0.397	0.322	0.107	0.344	0.603
Fraction Yoplait Store	0.481	0.318	0.205	0.474	0.766
Fraction Dannon UPC	0.095	0.034	0.077	0.097	0.118
Fraction Yoplait UPC	0.094	0.032	0.088	0.095	0.105
Price Difference	0.267	0.087	0.204	0.227	0.315

Notes: This table summarizes assortment, price at store level for multi-market retailers, across the three groups. Variables are defined in the same way as in Table B1.

B.3 Share and Price Variance Decomposition—All Brands

Table B4 shows market share and price variance decomposition results for all the products. The main conclusion that the Brand × Retailer component accounts for more than half of the total variance in share and price holds for all products.

Table B4: Market Share and Price Variance Decomposition
All Brands

	Panel A		Panel B	
	Share Decomposition		**Price Decomposition**	
	level	percentage	level	percentage
Total Variance	0.0002	100	0.038	100
Brand × Retailer	0.00015	56.75	0.022	57.94
Brand × Market	0.00005	21.26	0.001	27.96
Retailer	0.000	0	0.000	0
Market	0.000	0	0.001	3.61
R^2	0.891		0.832	
RMSE	0.007		0.099	

Notes: This table shows the results of AKM decomposition on market share and price of all brands at retailer-market level (Equation 1). Price is the price of yogurt of 6oz. Price and share are demeaned with brand average before the decomposition.

B.4 More Evidence of Potential Exclusion

A *more subtle form of exclusion* can take place if the captain takes advantage of its position and selects assortments that pose less competitive threats to its own products. As a result, a Dannon product in a Yoplait-led retailer can face fiercer competition than when it is in a Dannon-led retailer. We can test this hypothesis using a measure that proxies competition (or degree of substitution) between products. I first construct a Mahalanobis distance measure from product nutrition contents, which captures how close two products are in nutrition characteristics space within a store, then run the following regression at product pair(i,j) - store(s) level (let i denote Dannon or Yoplait product, j denote other products within the store), with the distance measure as dependent variable:

$$\text{dist}_{ijs} = \alpha + \beta \mathbb{1}\{\text{i is leading brand}\} \times \mathbb{1}\{\text{retailer r has a leading brand}\} \times \mathbb{1}\{\text{i j are different brands}\} + \gamma_b + \gamma_m + \epsilon_{is}$$

The three indicators respectively stands for whether the product is leading brand within chain, whether the retailer has a leading brand, and whether the products are owned by different brands. γ_b and γ_m are brand and market fixed effects. β is the parameter of interest.

The results are shown in Table B5: products sold in retailers not led by them face a shorter nutrition distance (thus a more intense competition) than in retailers led by them. Again without drawing any solid causal inference, I consider this evidence to be in line with the hypothesis that a category captain can manipulate product choices within retailer in order to shield its products from fierce competition.

Table B5: Test for Exclusion using Nutrition Distance

	(1) no mkt FE	(2) with mkt FE
brand_nolead × retailer_noled × diff brand	0	0
	(.)	(.)
brand_nolead × retailer_noled × same brand	-1.018***	-1.082***
	(-38.14)	(-40.45)
brand_nolead × retailer_led × diff brand	-0.0712***	-0.130***
	(-3.99)	(-6.32)
brand_nolead × retailer_led × same brand	-1.057***	-1.214***
	(-20.59)	(-23.09)
lead_brand × retailer_led × diff brand	0.0301	-0.0134
	(1.77)	(-0.65)
lead_brand × retailer_led × same brand	-0.242***	-0.336***
	(-5.72)	(-7.64)
DANNON	0	0
	(.)	(.)
YOPLAIT	-0.155***	-0.182***
	(-12.11)	(-14.08)
Constant	7.431***	7.461***
	(874.51)	(817.79)
Observations	723500	723500
R^2	0.003	0.005

t statistics in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

B.5 Case Studies

In this subsection, I present two case studies that zoom in to particular retailers and markets. The first one includes retailers whose leading brand changed over years, the second one looks into markets where Dannon-led and Yoplait-led retailers coexist.

Retailers whose Leading Brand Switched: Over the studied time period, there are three retailers whose market share leading brand switched between Dannon and Yoplait, and one of them underwent a merger.[37] With the change in leading brand, the market shares of the leaders was reversed. Using a difference-in-differences method, I first test whether the product assortment and promotions of products within the retailers changed significantly with the change of market share leader.

$$y_{bsrt} = \alpha_1 p_{bst} + \beta_1 I_t \times I_{br} + \gamma_b + \gamma_s + \gamma_t + \varepsilon_{bst}$$

where y_{bst} are the outcome variables including fraction of UPC of a parent brand, number of UPC-weeks of a parent brand that are on display, number of UPC-weeks of a parent brand that are featured. I_t is an indicator for years after switch, I_{br} is an indicator for the leading brand within chain after switch. I control for brand average price p_{bst} in the regression. γ_b, γ_s and γ_t denote brand, store, and year fixed effect.

[37] In retailer 29, share difference between Dannon and Yoplait went from -0.10 to 0.008. In retailer 866, it went from 0.16 to -0.15. In retailer 889, it went from 0.03 to -0.05.

Table B6 reports the results. The coefficients on fraction of UPC, number of week-UPCs featured, number of week-UPCs on sale are all significantly positive, suggesting that as the parent brand became the market share leader within chain, assortment and promotions also tended to favor that brand.

Table B6: DiD on Assortment Variables of Retailers that Switch Leader

VARIABLES	Fraction UPC	# display	# feature	# sale
After × Leading Brand (β_1)	0.0205***	-0.0683	0.258**	0.275***
	(0.00148)	(0.157)	(0.121)	(0.0406)
α_1	-0.0505***	-1.078***	-1.723***	-1.251***
	(0.00167)	(0.334)	(0.197)	(0.0669)
Constant	0.105***	2.013*	1.618*	1.429***
	(0.00896)	(1.101)	(0.914)	(0.420)
Observations	13,856	1,033	1,812	10,179
R-squared	0.921	0.649	0.806	0.839

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. Retailers 866, 6, 889 are used for these regressions. p is average price of 6oz UPCs of that brand.

On the other hand, I test whether the retailers' clientele showed any significant changes at the time of the switch:

$$y_{hrt} = \alpha_2 t + \beta_2 I_t + \gamma_{rt} + \varepsilon_{hrt}$$

where $\alpha_2 t$ is a yearly time trens, γ_{rt} is retailer-year fixed effect. I_t is an indicator for years after switch. I run this test on the set of households from Nielsen consumer panel data who purchased yogurt from these retailers. Table B7 shows the results of this test on four demographic variables: income, female age, female employment, and household size. The coefficients of I_t are all insignificant, except for household size which is slightly significant. The results suggest that these retailers which exhibited switch in market share leader did not experience significant changes in consumer demographic profiles, which indicates that demand condition may not be the main reason behind the market share flip.

Table B7: Demographic Remain Stable of Retailers that Switched Leading Brand

VARIABLES	Income	p-value	Female Age	p-value	Female Employ	p-value	Household Size	p-value
β_2	0.0312	0.763	0.984	0.253	0.0187	0.821	0.309*	0.0752
α_2	0.000873	0.976	0.489**	0.0422	-0.0157	0.497	-0.133***	0.00608
Constant	10.83***		52.34***		0.613***		2.606***	
Observations	12,302		11,006		11,006		12,302	
R-squared	0.003		0.194		0.004		0.015	
Number of household_code	4,514		4,090		4,090		4,514	

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. Income is logged household income. p-value is the p value of t-tests

Markets with Both Types of Retailers: The second case study focuses on markets where both Dannon-led and Yoplait-led retailers coexist. The hypothesis is that if the market share asymmetry is introduced by market segmentation associated with different demographic groups, then we will find that the two types of retailers probably cater to different consumers. To test this hypothesis, I run the following regression on a sample of DMAs where I observe both Dannon-led and Yoplait-led retailers:[38]

$$\text{logit}\left(\text{P(h visits retailer type k)}\right) = \beta_3 X_{ht} + \gamma_m + \gamma_r + \gamma_t + \varepsilon_{hrmt} \tag{33}$$

where X_{ht} are household demographic variables including female employment, income, household size and female age. γ_r, γ_m and γ_t are retailer, market and year fixed effects. Retailer type k refers to whether it is a Dannon-led retailer or Yoplait-led retailer.

The null hypothesis H_0 is $\beta_3 = 0$. Table B8 reports β_3 for separate demographic variables. They are not statistically different from zero, which implies that the demographic heterogeneity alone can not explain why there co-exit retailers that have stark difference in Dannon and Yoplait shares in the same market.

Table B8: Demographic Differences of Two Types of Retailers within Market

	(1)	(2)	(3)	(4)
Female Employ	0.0772			
	(0.0612)			
Income		0.00735		
		(0.0432)		
Household Size			-0.00659	
			(0.0216)	
Female Age				0.000443
				(0.00290)
Constant	1.566***	1.565***	1.661***	1.586***
	(0.0848)	(0.479)	(0.0907)	(0.171)
Observations	10,787	12,036	12,036	10,787

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses. Income is log income.

C Details of Stylized Supply Model

C.1 Proofs to Conclusions from Simple Model

In this subsection I provide proofs to the predictions of the stylized supply model presented in subsection 3.4.

[38] There are 41 DMAs over five years in the sample, with 1,084 households and 4.06 retailers on average.

Prediction (1). *The equilibrium market share of the captain is more than twice of that of the non-captain; and the market share asymmetry is proportional to the strength of substitution effect between the two brands.*

Take a ratio between the equilibrium quantities of brand 1 (the captain) and brand 2 (the non-CC): $\frac{q_1^{cc}}{q_2^{cc}} = \frac{\theta/4+1/2}{1/4} = \theta + 2 \geq 2$, since $\theta \geq 0$. As θ increases, substitution effect between the two brands gets stronger, the share asymmetry between captain and non-captain brands intensifies. This result is mainly driven by the price and quantity effect of eliminating double marginalization on captain brand.

Prediction (2). *non-captain brand is worse off under the other brand's captaincy than under retail category management. It sells less yogurt ($q_2^{cc} < q_2^{rcm}$), and its profit can be less than RCM case ($\Pi_2^{cc} < \Pi_2^{rcm}$).*

These results depend on substitution intensity between the two brands.

First, recall that $q_2^{cc} = \frac{1}{4}[(\theta-1)c+(\theta-1)\gamma^{cc}+1]$, $q_2^{rcm} = \frac{1}{2}[(\theta-1)w^{rcm}+(\theta-1)\gamma^{rcm}+1]$, and $\frac{\Pi_2^{cc}}{\Pi_2^{rcm}} = \frac{(2-\theta)[1+(\theta-1)\gamma^{cc}+(\theta-1)c]^2}{4[1+(\theta-1)\gamma^{rcm}+(\theta-1)c][1+(\theta-1)\gamma^{rcm}+(\theta-1)w^{rcm}]}$. Parameter values $\theta \in (0,1)$ and $\gamma^{cc} < \gamma^{rcm}$.

Whether or not $q_2^{cc} \leq q_2^{rcm}$ and $\frac{\Pi_2^{cc}}{\Pi_2^{rcm}} \leq 1$ depends on whether $w^{rcm} > c$: as θ increases, w^{rcm} increases over c, thus $q_2^{cc} \leq q_2^{rcm}$ and $\Pi_2^{cc} \leq \Pi_2^{rcm}$ will occur when θ gets bigger. That is, as substitution effect strengthens, non-CC brand will bear more loss if it is not selected as the captain, compared to RCM scenario.

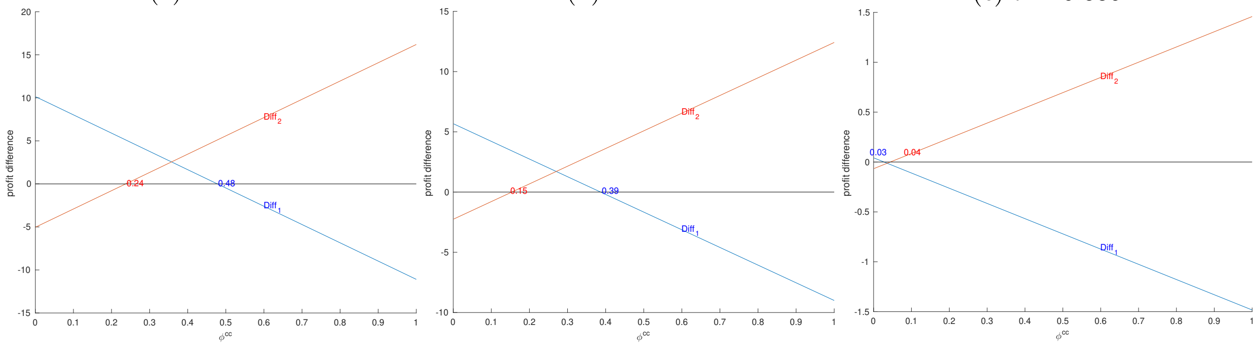
C.2 Comparative Statics

Two profit differences determine the equilibrium ϕ^{cc} in this symmetric game: $\text{Diff}_1 = (1-\phi^{cc})\Pi_A^{cc=1} - \Pi^{rcm}$ from inequalities (6) and $\text{Diff}_2 = \phi^{cc}\Pi_A^{cc=1} - \Pi_1^{cc=2}$ from inequalities (7). The equilibrium bid of the captain brand is $\frac{\Pi_1^{cc=2}}{\Pi_A^{cc=1}}$, at which $\text{Diff}_2 = 0$ and $\text{Diff}_1 \geq 0$.

Figure C1 shows comparative statics of the equilibrium ϕ with respect to changes in θ, the cross-elasticity parameter. The number in red is the equilibrium bid. As the substitution effect strengthens, the equilibrium bid decreases: the captain keeps less and less share of category profit to itself as the competition for captaincy gets fiercer. As θ increases to 0.835, the retailer will find it more profitable to manage the shelves by itself ($\text{Diff}_1 < 0$ at $\phi = 0.04$). (Notice here this result is partly driven by the parameterization. If c is set to be 1, $\text{Diff}_1 > 0$ at ϕ^{cc} for all $\theta \in (0,1)$).

Figure C1: Equilibrium Bid and Comparative Statics

(a) $\theta = 0.3$ (b) $\theta = 0.5$ (c) $\theta = 0.835$



Notes: This figure depicts first stage winning bid, and the comparative statics of the winning bid with respect to θ. Other parameters are: $c = 10$, $\gamma^{cc} = 0.5$, $\gamma^{rcm} = 1$

D Additional Results from Demand Estimation

D.1 Price Regressions; Instrumental Variables

Table D1 presents results from price regression, which generate predicted price ($\hat{p}$) to be used in demand IV constructions. I start with only product characteristics as independent variables, then add in transportation costs, input costs, main market characteristics, assortment variables. The improvement in R^2 is significant as these variables are added into the price regression, suggesting that these variables, especially transportation costs, assortment variables, are powerful exogenous factors that explain overall price variation. They will be used as price instruments.

Table D1: Price Regression

VARIABLES	(1) price	(2) price	(3) price	(4) price	(5) price	(6) price	(7) price
Fat	-0.0349***	-0.0393***	-0.0403***	-0.0431***	-0.0443***	-0.0355***	-0.0402***
	(0.00126)	(0.000920)	(0.00102)	(0.00113)	(0.00111)	(0.00113)	(0.00145)
Calorie	0.00427***	0.00587***	0.00582***	0.00628***	0.00625***	0.00473***	0.00623***
	(8.95e-05)	(6.59e-05)	(6.63e-05)	(7.79e-05)	(7.68e-05)	(7.82e-05)	(0.000104)
Sugar	-0.0202***	-0.0228***	-0.0186***	-0.0214***	-0.0233***	-0.0141***	-0.0164***
	(0.000372)	(0.000272)	(0.000540)	(0.000589)	(0.000585)	(0.000581)	(0.000795)
Sodium	-0.00293***	-0.00304***	-0.00307***	-0.00317***	-0.00311***	-0.00293***	-0.00330***
	(5.79e-05)	(4.57e-05)	(4.58e-05)	(5.64e-05)	(5.57e-05)	(5.59e-05)	(7.64e-05)
individual size	-0.0105***	-0.000441**	-0.000638***	-0.000506***	-0.000619***	-0.000308*	-0.00115***
	(0.000221)	(0.000178)	(0.000179)	(0.000179)	(0.000177)	(0.000169)	(0.000221)
Size	-0.00863***	0.0116***	0.0115***	0.0115***	0.0113***	0.0104***	0.00665***
	(0.000233)	(0.000225)	(0.000225)	(0.000224)	(0.000221)	(0.000285)	(0.000286)
organic	0.273***	0.279***	0.277***	0.242***	0.265***	0.302***	0.364***
	(0.00812)	(0.00883)	(0.00883)	(0.00944)	(0.00939)	(0.00991)	(0.0120)
Constant	1.661***	3.898***	3.880***	3.880***	3.886***	3.811***	3.711***
	(0.00735)	(0.0341)	(0.0341)	(0.0341)	(0.0336)	(0.0545)	(0.0542)
Observations	154,841	148,119	148,119	148,119	148,119	147,104	129,747
R-squared	0.788	0.892	0.892	0.892	0.896	0.920	0.955
Transportation cost	NO	YES	YES	YES	YES	YES	YES
Input cost	NO	NO	YES	YES	YES	YES	YES
Mainmkt	NO	NO	NO	YES	YES	YES	YES
Assortment	NO	NO	NO	NO	YES	YES	YES
Product FE	YES	YES	YES	YES	YES	YES	YES
Retmkt FE	YES	YES	YES	YES	YES	YES	YES
Retmkt-brand FE	NO	NO	NO	NO	NO	YES	YES
Retmkt-product FE	NO	NO	NO	NO	NO	NO	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Logit specification tests and Lasso are used to select instrumental variables for demand estimation. A complete list of instrumental variables used in demand estimation is presented in Table D2. In total, number of price IVs is 26, number of differentiation IVs is 29.

Table D2: Instrumental Variables for Demand Estimation

Price IV	Input price × product chars Transportation: diesel price × distance, size × distance Retailer-brand main market chars × product chars Assortment: nbupc, nbsize etc.
Differentiation IV	$\sum_{j' \in J_{rmt}} (1\|x_{j'rmt} - x_{jrmt}\| < std)$; $mean(demo) \times x$; $\sum_{j' \in J_{rmt}} (1\|x_{j'rmt} - x_{jrmt}\| < std) \times std(demo)$; $\sum_{j' \in J_{rmt}} (1\|x1_{j'rmt} - x1_{jrmt}\| < std) \times std(demo) \times (x2_{j'rmt} - x2_{jrmt})$

D.2 Marginal Cost, Margins under Bertrand-Nash

Assuming Bertrand-Nash price competition, I back out retail margin and margins. Average margins is around 22%, similar to other applications using yogurt data. In Table D3, I regress implied retail marginal costs on retailer characteristics, product characteristics, and retailer-brand fixed effect estimated from the model. Marginal costs are negatively correlated with retailer geographical coverage, due to economics of scale. Fraction of premium UPCs is a measure of the luxuriousness of the retailer, and it is positively correlated with marginal cost. Retailers that are serving a higher income group have higher marginal cost. Results in column (2) suggest that it is more costly to produce healthier yogurt (yogurt with less sugar, sodium and fat) and organic yogurt.

Table D3: Correlation between MC and Product, Retailer Characteristics

	MC	MC	MC	Price
retailer coverage	-0.0551***	-0.0515***	-0.0482***	-0.0481***
	(0.00238)	(0.00197)	(0.00197)	(0.00197)
fraction of premium upc	2.487***	0.243***	0.288***	0.304***
	(0.103)	(0.0861)	(0.0860)	(0.0860)
retailer income	0.141***	0.111***	0.0907***	0.0913***
	(0.0143)	(0.0118)	(0.0119)	(0.0119)
Sugar		-0.0351***	-0.0348***	-0.0347***
		(0.000237)	(0.000237)	(0.000237)
Sodium		-0.00562***	-0.00562***	-0.00554***
		(3.42e-05)	(3.41e-05)	(3.42e-05)
Fat		-0.0122***	-0.0124***	-0.0130***
		(0.000544)	(0.000543)	(0.000543)
Calorie		0.00522***	0.00519***	0.00524***
		(5.28e-05)	(5.28e-05)	(5.28e-05)
organic		0.431***	0.435***	0.433***
		(0.00357)	(0.00357)	(0.00357)
nbflavor		-0.00800***	-0.00804***	-0.00794***
		(0.000199)	(0.000198)	(0.000198)
Retbr_fe			0.0132***	0.0146***
			(0.000562)	(0.000562)
Constant	1.014***	1.488***	1.474***	1.717***
	(0.00696)	(0.00713)	(0.00714)	(0.00714)
Observations	154,069	154,069	154,069	154,069
R-squared	0.052	0.354	0.356	0.353

Notes: Standard errors in parentheses

E Gibbs Sampler—Convergence Property

Bayesian inference literature usually uses diagnostic graphs to check convergence property of MCMC methods. The three panels in Figure E1 depict moving averages of the estimated probability p, shelf advantage parameters β, and variance σ. The moving average is calculated at 100 incremental of iterations (the first average is 1 to 100, the second is 1 to 200, etc). The Markov chain starts to converge after about 100 - 500 iterations.

Figure E1: Moving Average of Estimated Parameters from Gibbs Sampler

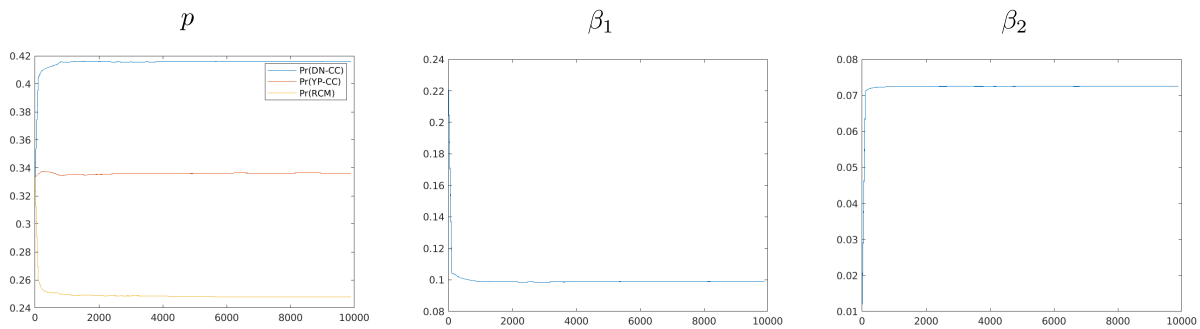


Figure E2 and Figure E3 present trace plots for the three probabilities and two parameters. The Gibbs sampler seems to mix well after a burn-in period of about 500 iterations.

Figure E2: Trace of Estimated Probabilities

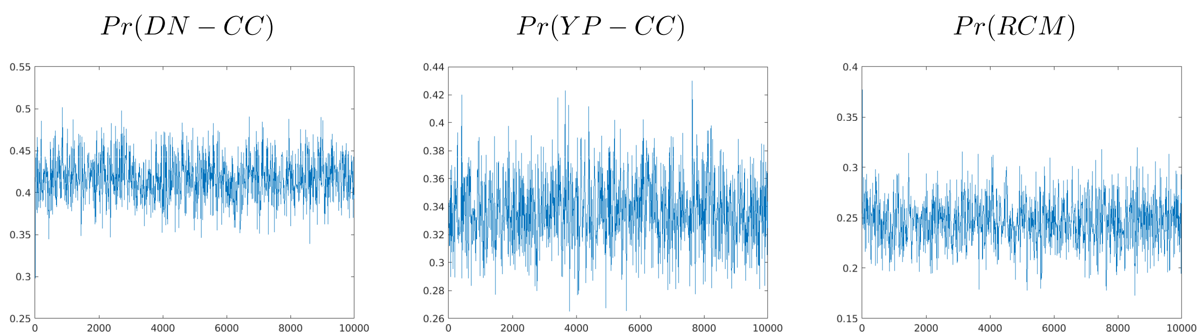


Figure E3: Trace of Estimated Parameters

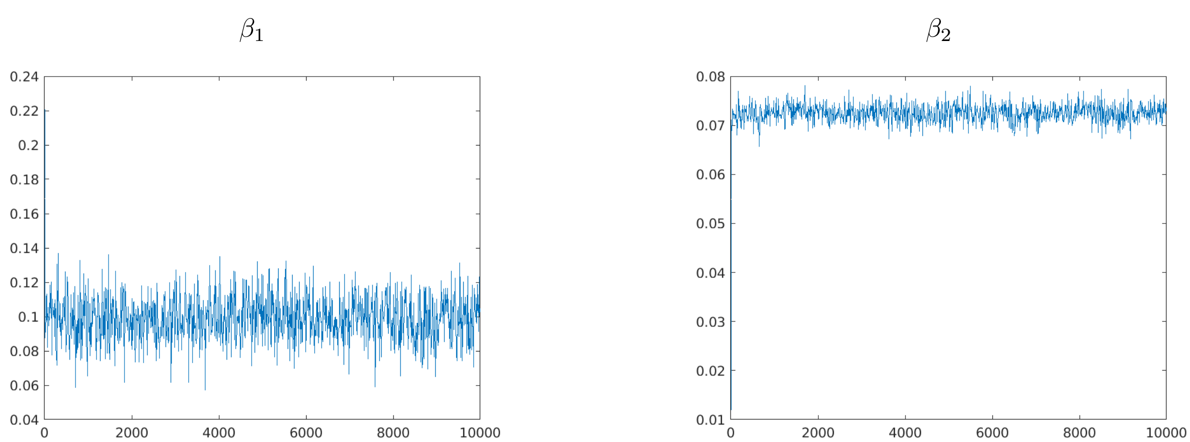
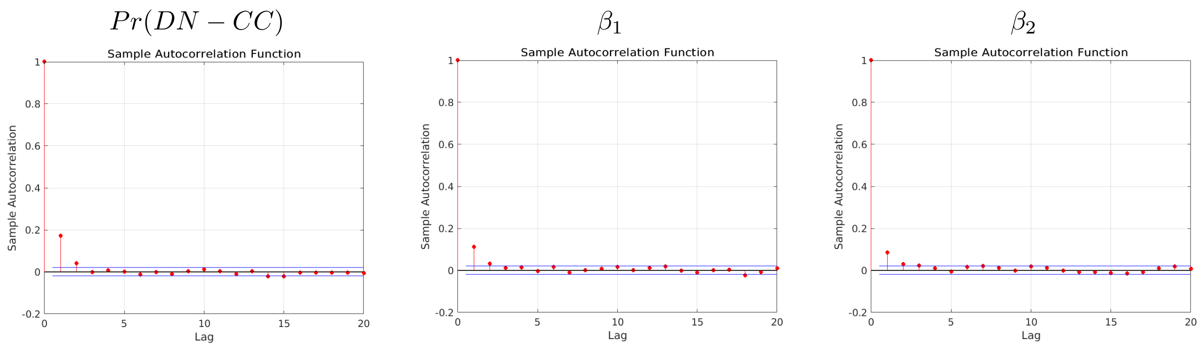


Figure E4 plot auto-correlations between the samples returned by the Gibbs sampler. The lag-k autocorrelation is the correlation between every sample and the sample k steps before. The autocorrelations from my Marcov chain becomes smaller as k increases, i.e., the samples can be considered as independent. The low degree of correlation between samples indicates fast mixing.

Figure E4: Auto-correlation of Estimated Parameters



F More on Classification Results

F.1 Stability of Gibbs Classification

There are in total 63 retailers observed for more than one year in the sample. For these retailers, I calculate the number of years when its classified captaincy status switches relative to the total number of years it is in the sample. Table F1 summarizes the number of retailers that do not switch captaincy status (the first column), and the number of retailers that switch (Percent Year Switch). 63.49% of retailers are consistently predicted to be in one captaincy type across the years they are in the sample. This indicates that the classification results from Gibbs sampler do not have too much noise.

Table F1: Stability of Classification over time

Percent Year Switch (%)	0	20	25	33	40	60
Nb Retailer	40	9	1	1	11	1

F.2 Retailer Characteristics of Classified Retailers

Table F2 shows comparison of retailer characteristics between classified RCM retailers and retailers with a captain, including retailer size (total UPCs, total revenue), number of markets, and presence of store brands. The RCM retailers are larger, manage more products, and carry more store brands. This observation is consistent with the industry view that the RCM retailers are more sophisticated. They are more likely to negotiate better deals with brands, and are more efficient in managing the shelves.

Table F2: Retailer Characteristics of RCM Retailers v.s. Captain Retailers

	RCM retailers	**Captain retailers**	**p-value**
total UPCs (in ten million)	0.934	0.535	0.0133
total revenue (in million dollars)	4759.576	2401.863	0.0007
number store	204.555	142.502	0.0538
fraction UPC of store brand	0.161	0.119	0.094

In Table 15 I show that the price difference between Dannon and Yoplait is smaller in Dannon-captained retailers than in Yoplait-captained retailers. Here I estimate similar regressions (Equation 34) but using the price/assortment difference between Dannon and all the other brands in the retailer as independent variables. Prob $(\text{DN-CC})_r$ is the estimated probability of a retailer having Dannon as a captain, and DX_r are differences in average price and assortment between Dannon and all the other brands within the same retailer. Table F3 reports the regression results, which suggest that a higher probability of Dannon as a captain is positively correlated with lower price and larger assortment of Dannon.

$$\text{Prob } (\text{DN-CC})_r = \alpha + \beta \text{DX}_r + \epsilon_r \tag{34}$$

Table F3: Asymmetry in Shares, Assortments and Prices between Dannon and the other brands in Classified Captain Retaielrs

Dep: Prob (Dannon-Captained)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ξ Diff	0.669***						
Share Diff		1.268**					
Frac UPC Diff			3.147***				
Nb Size Diff				0.949***			
Nb Flavor Diff					0.239***		
Nb Sales Diff						0.0200***	
Price Diff							-0.823***
Constant	0.535***	0.631***	0.664***	0.452***	0.653***	0.457***	0.480***
Observations	225	225	225	225	225	225	225
R-squared	0.095	0.025	0.685	0.078	0.397	0.033	0.109

Notes: This table reports regression results from Equation 34. Each column is a regression with a different dependent variable. Standard error in parenthesis.

F.3 Overlap between Deterministic and Gibbs Classification

Table F4 shows the number of retailer-year (note that the classification is year-specific) classified into Dannon captain, Yoplait captain, and RCM, by deterministic rule and Gibbs sampler. The third row shows the number of retailer-year that are classified into the same type by both rules. The overlap is big.

Table F4: Overlap of Retailers between Deterministic and Gibbs Classification Results

	DN-CC	YP-CC	RCM
Deterministic	68	132	106
Gibbs sampler	118	107	81
Overlap	56	94	47

G Conduct Tests with Deterministic Classification

In section 5 I present and discuss the conduct test results using classification information from Gibbs sampler. Here I show conduct test results using classification from the deterministic classification rule (see subsection 4.2 for definition of deterministic classification rule).

Table G1 reports Rivers-Vuong test results for all the retailers. Table G2 reports the results for retailers classified as having a captaincy arrangement. And Table G3 reports the results for RCM retailers. Qualitatively, the conclusions from these sets of results using deterministic classification are similar to those in section 5 using Gibbs sampler.

Table G1: Rivers-Vuong Test Results for All Retailers
—Deterministic Classification

Null	Alternative	H(2) All with DM	H(3) All zero WPCM	H(4) All zero RPCM	H(5) DN & YP no DM	H(6) CC retailer Collude
H(1). CC Pricing	*Test Statistic*	-9.2620	-10.0216	-11.5281	-0.8940	-2.8162

Notes: This table reports test statistics from Rivers-Vuong test for all the retailers in the sample. The tests are conducted based on the deterministic classification results.

Table G2: Rivers-Vuong Test Results for Retailers with Captain
—Deterministic Classification

Null	Alternative	H(2) All DM	H(3) All zero WPCM	H(4) All zero RPCM	H(5) DN & YP no DM	H(6) CC retailer Collude	H(7) Opposite CC
H(1). CC Pricing	*Test Statistic*	-2.6684	-5.8408	-9.3484	-5.1057	-4.5001	-1.3436

Notes: This table reports Rivers-Vuong Test statistic on retailers with a captain. The tests are conducted based on the deterministic classification results.

Table G3: Rivers-Vuong Test Results for Retailers without Captain
—Deterministic Classification

Null	Alternative	H(0) DN CC	H(1) YP CC	H(3) All zero WPCM	H(4) All zero RPCM	H(5) DN & YP no DM	H(6) CC retailer Collude
H(2). All DM	*Test Statistic*	4.0256	1.8379	0.4362	-3.0065	5.5002	2.2429

Notes: This table reports Rivers-Vuong Test statistic on retailers without captaincy arrangement (RCM retailers). The tests are conducted based on deterministic classification results.