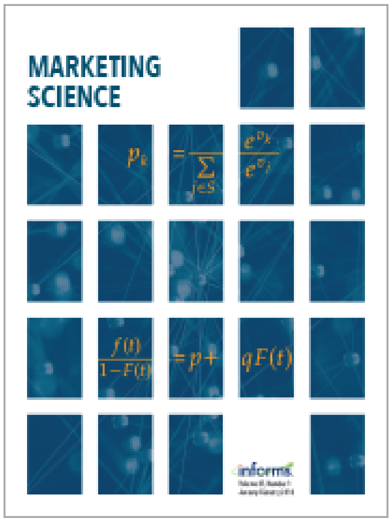

Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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informs
http://pubsonline.informs.org/journal/mksc

MARKETING SCIENCE
Vol. 40, No. 2, March–April 2021, pp. 261–282
ISSN 0732-2399 (print), ISSN 1526-548X (online)

Economic Impact of Category Captaincy: An Examination of Assortments and Prices

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Received: March 30, 2016
Revised: October 19, 2017; September 9, 2019
Accepted: February 8, 2020
Published Online in Articles in Advance: October 19, 2020

https://doi.org/10.1287/mksc.2020.1251

Abstract. We empirically investigate the impact of *category captaincy*, an arrangement where the retailer works exclusively with a manufacturer to manage both the manufacturer's and his rivals' products. Using a unique data set that contains information on category captaincy as well as SKU-store-level sales and price across 24 retail chains and eight local markets in the United States for a frozen food category, we quantify the impact of captaincy on prices, assortments, profits, and consumer welfare. Interestingly, our estimates suggest that captaincy can lead to welfare gains for consumers, which argues against a purely negative view of captaincy by policy makers.

History: K. Sudhir served as the senior editor and Harikesh Nair served as associate editor for this article.
Supplemental Material: Data and the online appendices are available at https://doi.org/10.1287/mksc.2020.1251.

Keywords: moment inequalities • category management • structural models • retail • category captaincy

1. Introduction

Intensive price competition, new advances in technology, and highly demanding consumers are forcing retailers to enter into innovative arrangements with manufacturers to improve profit margins. One such arrangement that has become increasingly popular in the food and drug retail industry, ranging from slow-moving categories like hair and skin care products to fast-moving categories like fresh produce, is *category captaincy* (Dudlicek 2014).

Category captaincy is an arrangement between a retailer and a manufacturer in a particular category, wherein the chosen manufacturer influences pricing and assortment decisions for all products in the category (Desrochers et al. 2003). The category captain may also assist in analyzing, developing, and implementing category plans. This is a task that has, for long, been performed by retailers who analyze category level data and allocate scarce resources across products within the category to leverage assets such as shelf space and customer traffic (Blattberg and Fox 1995, Basuroy et al. 2001, Gajanan et al. 2007).

Over the years, the massive increase in the number of categories and products within a category has meant that most retailers find themselves lacking the resources and capabilities to implement category management efficiently across all the categories they manage (Morgan et al. 2007). On the other hand, manufacturers have developed considerable expertise in efficient assortment planning, pricing, and promotions. This has led to an increase in the popularity of category captaincy arrangements.

Under category captaincy, the designated manufacturer (captain) undertakes joint responsibility with the retailer for developing and growing the category. The captain is provided access to proprietary sales information for the entire category by the retailer, in exchange for developing a category plan that encompasses all the stock keeping units (SKUs) in the category, including those of his rivals. The captain combines the data provided by the retailer with his category management expertise to provide specific recommendations on growing the category. These recommendations include the addition and removal of SKUs and shelf placements of various SKUs in the category (Gruen and Shah 2000). An appropriate way to think of captaincy is as a transfer of decision rights (pricing, assortments, category services) from the retailer to the captain. 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, for example, by allocating personnel and money to the task (FTC 2001).

Intuitively, there is a trade-off at the heart of any category captaincy arrangement. The benefits of captaincy rely on the argument that manufacturers know much more about an individual category than even the largest retail chains. The arrangement can be efficiency-enhancing and beneficial to channel members and consumers if captains increase channel coordination, provide new services, or generally operate at lower costs (relative to retailer management). On the other hand, there is also significant concern that category captains can use their special status with retailers to significantly affect the pricing and availability of products on the shelf, undermine competition, and consequently hurt consumers. (Gruen and Shah 2000, FTC 2001, Lindblom and Olkkonen 2008).[1]

A relatively sparse literature on category captaincy has looked at factors that impact this trade-off.[2] Kurtulus and Toktay (2011) examine category captaincy with pricing decisions delegated to category captains under conditions of limited shelf space. The main advantage of captaincy in their setting is to improve vertical channel coordination. Retailers use a combination of captaincy and shelf space to control the intensity of competition and to restrain the captain from foreclosing activities. Captaincy arrangements, in this context, are profitable for the channel depending on the degree of product differentiation, the opportunity cost of shelf space, and the profit-sharing arrangement between the retailer and the captain. Nijs et al. (2014) also look at captaincy in terms of a transfer of pricing authority to the captain and find that the main benefit of captaincy is through the ability of the captain to share price information, both horizontally across retailers and vertically within channel members, to improve price coordination. They suggest that appointing a captain who sets retail prices is socially beneficial only if the captain is permitted to coordinate wholesale and retail prices across manufacturers and retailers. If firewalls prevent vertical and horizontal coordination, then captaincy arrangements are socially inefficient.

Whereas the aforementioned papers examined the role of captaincy with pricing decisions as the focus, another set of papers focused on decisions related to nonprice dimensions such as assortment choices (Kurtulus and Toktay 2011) and demand-enhancing services (Subramanian et al. 2010). For instance, Subramanian et al. (2010) show that, when category captains can undertake demand-enhancing services, appointing a captain always benefits the retailer; manufacturers benefit only when the cross-price elasticity of competing products in the category is sufficiently high. For low levels of cross-price elasticity, captaincy arrangements may hurt the noncaptain manufacturer and even the captain himself. Kurtulus and Toktay (2011) compare the assortment choices made by the retailer versus those made by a manufacturer appointed as a captain. Their analytical results show that a captain's assortment choices can be larger or smaller than the retailer's assortment choices. Nevertheless, the captain's assortment choices generally improve profits for all concerned. The consensus from the aforementioned theoretical papers seems to suggest that captaincy arrangements are efficiency-enhancing. This is supported by one of the few empirical studies in this area. In a large-scale survey of retailers, Gooner et al. (2011) find that more "intensive" engagement with appointed captains improved the retailers' own financial outcomes. Additionally, these retailers report no significant evidence of abusive behavior by appointed captains or evidence of negative reactions from the noncaptain manufacturers.

Summary

The analytical work reviewed above suggests that captaincy has multiple, plausibly different effects on four important sets of actors; retailers: the captain, noncaptain manufacturers, and consumers. To presage our analysis, it is useful to club these effects into three categories. On the plus side, captaincy could lead to greater *efficiency*, because of the manufacturer's being able to perform category management tasks at a lower cost than the retailer. As a result of these lower costs, it might well be that the optimal assortment suggested by the manufacturer is larger than what was feasible for the retailer. In other words, the *market coverage* increases. On the negative side, the captain might take actions that would benefit him at the expense of his rival manufacturers—most prominently, he could *substitute* rivals' products for his own, leading to profit losses for the rivals. An appropriate evaluation of category captaincy would thus need to explicitly understand and quantify the magnitudes of these three effects—*efficiency*, *market coverage*, and *substitution*—on the four sets of actors listed above. This has hitherto not been attempted in prior literature because (a) the assortment decision and its subsequent impact on pricing has generally not been considered; and (b) captain and noncaptain arrangements have not been considered jointly in any empirical work, making it difficult to draw robust conclusions.

Each of these points is vital. To take the first, if one only considers price, as most prior literature has done, one runs the risk of concluding that a higher price after captaincy is due to anticompetitive motives. This is erroneous because it could be improvements in nonprice elements (most obviously, enhanced assortment) that led to this price increase. To take the second point, one cannot obtain an unbiased evaluation of the impact of captaincy by only looking at retail chains that have adopted this practice, for obvious reasons of selection bias.

Our Research

We evaluate the impact of category captaincy arrangements by addressing the following questions empirically: (i) Does the category captain impact the overall size of product assortments? (ii) Does the category captain selectively alter the assortment to favor his own products over those of his rivals? (iii) Do retail prices increase or decrease under category captaincy? (iv) Does social welfare increase or decrease under category captaincy?

There are two challenges to overcome. First, to empirically assess category captaincy arrangements, one requires data on captaincy status. As previous research (Gajanan et al. 2007, Nijs et al. 2014) notes, these data are very sensitive and not readily available. Second, even with sufficient data, empirical analysis is difficult because many aspects, such as payments between manufacturers and retailers, are typically not observed. The challenge then is to recover these payments from observable measures of market structure and demand. This, in turn, requires (i) a rich demand model that captures variation in consumer preferences; (ii) a supply model of assortment and prices that embeds both horizontal interaction between competing manufacturers and vertical interactions between manufacturers and retailers; and (iii) a captaincy selection model that addresses the choice of captain. The second and third requirements, in particular, pose significant methodological challenges, as evidenced by the very limited number of extant studies examining assortment selection (e.g., Misra 2008, Draganska et al. 2009)[3] and the absence of studies on captaincy selection.

To address our research questions and overcome the challenges above, we worked with a frozen food manufacturer to assemble a unique set of data from multiple sources.[4] The data include information on category captaincy status, as well as SKU-store-level sales and price, across 24 retail chains in the United States over multiple years. We use this to estimate a structural model that focuses on retail assortments and prices, while accounting for the key institutional features of the category being studied.

The model consists of four parts: (i) a *demand* submodel that accommodates heterogeneity in consumer preferences; (ii) a *pricing* submodel that accommodates competition between manufacturers, and vertical interactions between manufacturers and retailers; (iii) an *assortment decision* submodel that captures differences in this decision between a retailer and a category captain; and (iv) a *captaincy selection decision* submodel that accommodates the decision of a manufacturer and retailer to enter into a captaincy arrangement.

The demand model allows us to characterize the impact on sales of adding or removing an SKU from the assortment across the set of items offered by the retailer. To obtain the marginal cost of every item, estimated demand parameters are combined with standard assumptions on channel pricing. The pricing model allows us to characterize the pricing response for a given assortment. The assortment model focuses on the assortment choice itself and allows us to characterize the fixed cost per period of adding an item to the assortment. Finally, the captaincy selection model focuses on the manufacturer's and retailer's incentives to enter into a captaincy arrangement and allows us to characterize the amount that the manufacturer is willing to pay the retailer for captaincy.

To obtain the amount that the manufacturer is willing to pay the retailer for the right to be captain and the fixed cost of carrying an item, we use an inequalities estimator (Albuquerque and Bronnenberg 2012, Chan and Park 2015, Pakes et al. 2015). The inequalities are generated by the necessary conditions obtained from the assortment decision and captaincy selection decision submodels. The necessary condition from the captaincy selection decision submodel, that manufacturers and retailers enter into a captaincy arrangement conditional on their expectations regarding profits in all other possible arrangements, is used to obtain the amount that manufacturers are willing to pay the retailer for becoming captain. This methodology is particularly useful for solving discrete choice games, where uniqueness of equilibrium is not guaranteed. The necessary condition from the assortment decision submodel, that category captains (or retailers) choose assortments conditional on their expectations regarding other possible assortment choices and prices, is used to obtain the fixed cost of carrying an item.

The four components of the model allow us to estimate unobservable factors of interest, such as consumer preferences, as well as marginal and fixed costs. Using these estimates, we proceed to assess the new equilibrium that would result in moving from a retailer management setting to a category captaincy setting. This counterfactual calculation allows us to characterize the changes in the size and composition of the assortment, as well as changes in the retail price, and consequently in consumer welfare and channel profits. These changes help us assess the magnitude of each of the effects referred to earlier and thus assess the impact of category captaincy. To reiterate, the effects we study are an *efficiency effect* that occurs if the shift to captaincy lowers the upfront fixed cost per period; a *market-coverage effect* due to the addition of SKUs that a retailer would have otherwise not carried; and a *substitution effect* due to a rival manufacturer's SKUs being dropped from the assortment carried. Together, these effects determine the products available to the consumers under category captain arrangements.

Before we preview our results, it is important to highlight a limitation of our empirical exercise. Clearly, an important aspect of category captaincy is the selection of the captain. This is a decision by the retailer and could depend on a number of factors. Normally, to account for this selection nonparametrically, one would use a variable that independently affects the retailer choice of captaincy but does not affect the outcomes (prices, assortments, and profits). We do not have data with such variation, which precludes the obvious approach just outlined. Instead, we use a structural model that characterizes the incentives of the retailer and the manufacturer to enter into a captaincy arrangement. To make the estimation tractable, we make two major assumptions. First, we restrict the set of possible retail assortments under different captaincy arrangements to a fixed predetermined set. Second, we assume that profits from this predetermined set follow a logit distribution. These two assumptions create the problems typically associated with the selection of choice sets and logits, that is, the independence of irrelevant alternatives (IIA). Any irrelevant option in the construction of the choice set could bias our results. That said, if the possible set of alternatives is large (as is in our case), then the bias is mitigated as each choice alternative contributes only a small amount to the likelihood. Nevertheless, we conduct a number of robustness checks by relaxing the assumptions above.

Preview of Findings and Contributions

We find evidence for all three of the effects mentioned above. First, our results show a strong efficiency effect; that is, we find a lower fixed cost per period per SKU under captaincy than under retailer management. This comports with the industry conjecture (e.g., Desrochers 2003) that even large retailers face a cost disadvantage compared with manufacturers in undertaking the assortment decision because of the sheer number of categories that confronts retailers. Second, we find evidence for the market coverage effect—in our data, captaincy always leads to the introduction of SKUs that the retailer would not have otherwise carried. Third, under category captaincy, the SKUs included in the assortment favor the captain, which is evidence for the substitution effect. On the issue of firm-level profits, retailers always benefit from captaincy arrangements; by contrast, not all manufacturers gain, particularly not the closest rivals of the appointed captain. Consumer welfare goes up in some circumstances, as does overall social welfare, suggesting that category captaincy is presumptively a procompetitive development in channels.

To the best of our knowledge, this is the first paper that empirically examines the role of category captain arrangements on assortments and quantifies their impact on consumers and various channel actors. Our paper is relevant to academics who study related vertical ties, such as exclusive dealing and slotting allowances. Prior empirical studies have primarily focused on the role of price in these manufacturer–supplier arrangements—our research is the first to isolate the impact on nonprice aspects. Methodologically, our study adds to the small body of work in marketing that seeks to structurally estimate the parameters of both assortments and pricing decisions (Misra 2008, Draganska et al. 2009). Managerially, our research is of importance to manufacturers and retailers in understanding the costs and benefits of these vertical arrangements. Finally, policy makers are constantly scrutinizing many of these arrangements for possible threats to competition, particularly consumer welfare reductions arising from an increase in retail prices or a reduction in SKUs. Our model can be usefully employed for this purpose. That said, it is important to emphasize that the lack of much variation in captaincy arrangements in our data means that caution is warranted in applying our conclusions to other contexts.

2. Data Description

Our data come from a major manufacturer in a large, frozen food category in the U.S. grocery retail trade.[5] The category is dominated by two national brand manufacturers who account for almost 75% of dollar sales. Private labels account for about 11% of total sales volume. This setting offers several advantages for studying category captaincy. First, the product attributes (brands, flavors, sizes) can be summarized quite comprehensively, facilitating the accurate characterization of consumer preferences. Second, as mentioned earlier, the major manufacturers in this category utilize a direct-store-delivery (DSD) distribution system. Thanks to individual manufacturers taking care of delivery and inventory-stocking for their own products in a DSD system anyway, a change in the captaincy arrangement mainly shifts the assortment decision from the retailer to the appointed captain. Consequently, an empirical model that focuses on the transfer of assortment decision authority from retailer to captain is an accurate characterization of our setting.

2.1. Data and Variables

We have store-level movement data for 24 grocery retail chains (not including Walmart or Target) from AC Neilsen's *Storeview* database. The store-level data cover major geographic markets in the United States. In each of these markets, we observe the price, volume, SKU number, and description at the store-week level, for the 21-month period from March 2010 to December 2011.

With the assistance of the manufacturer, we hand-assembled the status of category captaincy (i.e., whether present or not, and if yes, the identity of the captain) at each of the retail chains over the same 21-month period. The captaincy data limit our focus to eight geographic markets. In these eight geographic markets, we find chains with and without category captain arrangements, as well as those in which the identity of the captain changed.

2.2. Preliminaries

Our objective is to model the relationship between captaincy arrangements, assortments, prices, and consumer demand. Given the importance of assortments to our model, it is important to explain how we measure assortment choices and market sizes.

Assortments. We denote an SKU as part of the assortment at a given chain-market-quarter if that SKU's sales are nonzero (Misra 2008) in a given quarter. Table 1 describes the assortment sizes in our data. Assortment size varies considerably across chains within markets, averaging around 50 SKUs. To put this into perspective, the total number of unique SKUs within a market (denoted as the *assortment superset*) varies from 60 to 80 across markets. This variation is crucial to our analysis, as we model each chain's assortment as being chosen from the relevant market superset. In other words, all chains choose from a common set of products that is available to all of them in that quarter.

Chain-Market Size. The total number of households in each market is shown in Table 1. However, this raw number does not account for the fact that the number and location of stores differs by chain even within the same market. To correct this, we identify the geolocation of each store and obtain the total number of households in that store's zip code from census data. We then aggregate these household numbers across all stores of that chain within a market to arrive at the chain-market size measure.

2.3. Model-Free Evidence

Before invoking the theoretical model and undertaking econometric analyses, we present descriptive results linking category captaincy to sales, market share, assortments, and prices. We show the variation at three levels—chain, chain manufacturer, and chain brand. At each one of these levels, we examine the impact of captaincy arrangements on assortments, price, and sales. In addition, for the manufacturer and brand-level analysis, we compute z-scores for assortments, prices, and market shares, and examine the distribution of these z-scores across captaincy arrangements. This is done to provide for easy comparison across products, time, and chains. Following the descriptives of the raw data, we run a series of simple ordinary least squares (OLS) regressions for each of the outcomes.[6] Our goal is to present model-free evidence that suggests captaincy arrangements indeed affect performance in this category. It is important to note that the evidence is only suggestive of the relationships between captaincy arrangements and the different marketing mix variables and is not meant to imply causality.

2.3.1. Descriptives. ***Sales and Assortments—Chain Level.*** Table 2 shows that, on average, category captaincy is associated with larger chains (whether measured as Nielsen store size, number of stores, or a composite index). Category captaincy, on average, is also associated with higher category sales and larger assortment sizes (see Table 3). Table A.1 in Online Appendix A contains a reduced form specification that controls for time and chain fixed effects. The impact of captaincy on total chain sales is positive but insignificant ($p > 0.10$). The impact on total assortments carried by the chain is positive and significant ($p < 0.10$). This variation in assortment sizes between stores managed by retailers versus those managed by captains will be crucial to our identification strategy later.

Market Shares, Prices, and Assortments—Chain Manufacturer Level. Tables A.2, A.3, and A.4 in Online Appendix A show the z-scores for assortments, prices, and market shares for different manufacturers under different captaincy arrangements. First, the total number of products for different manufacturers is highest under their own captaincy (diagonal elements). Second, there are differences in the distribution of prices, and consequently market shares, for the manufacturers under different captaincy arrangements. Prices for firm B are higher under its own captaincy arrangement, whereas those of firm A are lower. In fact, prices for firm B are lowest under the retailer arrangement. Coming to market shares, although both firm A and firm B have higher market shares under their own

Table 1. Descriptive Results by Markets

Geographic market	Number of chains	Number of captaincy chains	Market size (average households)	Number of SKUs in market (assortment superset)	Number of SKUs in chain (assortment carried)
Baltimore	4	2	218,403	89	59
Raleigh	3	2	260,683	78	64
Erie	2	1	49,900	60	48
Las Vegas	4	3	124,670	72	50
Los Angeles	4	3	429,938	70	51
New York	5	4	181,372	74	53
Poughkeepsie	3	2	33,097	76	52
San Diego	4	3	247,263	78	56

Note. Averages are across chain-quarter.

Table 2. Distribution of Captaincy Arrangements Across Store Size

	Captaincy arrangement		
Store Size Quartiles (ascending)	Firm A–captain	Firm B–captain	Retailer
First quartile	0%	26%	74%
Second quartile	11%	81%	8%
Third quartile	65%	9%	25%
Fourth quartile	42%	26%	31%

captaincy arrangement relative to captaincy by their rivals, firm B's market share is higher when the retailer is managing the category. These results can be reconciled by noting that firm B is the smaller manufacturer, with a smaller portfolio of products and a smaller market share. All else equal, firm B would prefer retailer-managed stores; however, conditional on the retailer opting for a captaincy arrangement, firm B is better off being a captain. The model-free evidence is supplemented by reduced form results in Table 4 (OLS regressions at the manufacturer level). The total number of products for a manufacturer goes up under its own captaincy, whereas prices and market shares of the captain's products are lower but insignificantly so.

Market Shares, Prices, and Assortments—Chain Brand Level. Table 5 shows the *z*-scores for assortments, prices, and market shares for different manufacturers under different captaincy arrangements at the brand level. Firm A owns two brands, whereas firm B owns only one brand. On assortments, captaincy arrangements always have a higher number of the captain's brands and a lower number of the rival's brands. Prices for both of firm A's brands are lower, whereas those of firm B's brand are higher under their respective captaincy arrangements. Market shares reveal a more interesting story on firm A. The lower priced brand of firm A has a lower market share than the higher priced brand of firm A under its captaincy arrangement. This, along with the corresponding decrease in prices and increase in assortments, suggests that firm A is trying to differentiate the market further in chains that it manages. This point is reinforced by examining the corresponding shares of firm A's two brands under firm B's captaincy. The higher-priced brand of firm A competes more with firm B's brand and sees a corresponding decrease in market share, whereas the lower-priced brand sees a small increase. The reduced form results in Table 4 (OLS regressions at the brand level) reinforce the impact of captaincy on assortments. The total number of products for a brand goes up under its own captaincy, whereas prices are higher and market shares of the captain's products are lower, but insignificantly so.

Summarizing, chains with category captaincy, on average, (i) are larger in size, (ii) have larger category sales, (iii) carry larger assortments, and (iv) carry a disproportionately larger portion of the captain's SKUs. However, this summary description masks differences in the identity of the manufacturer acting as the category captain. These differences are revealed by our subsequent analysis at the chain, manufacturer, and brand levels. At the chain-manufacturer level, assortments and market shares of the captain are higher under his own captaincy than when his rival is the captain. However, firm B (the smaller manufacturer) has a higher market share under retailer management than under its own captaincy. This suggests that firm B would prefer retailer managed stores, but, conditional on the retailer opting for a captaincy arrangement, is better off being a captain. This notion is supported by the fact that a manufacturer's assortments and market share go down under the rival manufacturer's captaincy. The analysis at the chain-brand level reinforces several of these claims. The captain's assortments are higher under his captaincy as opposed to under his rival's captaincy.

2.3.2. Further Evidence. In the majority of our data, we only observe chains under one arrangement (either retailer management or category captaincy (CC)). This makes our findings subject to a criticism of reverse causality, namely, that higher market shares or assortment shares led to category captaincy arrangements, not the reverse. Given the nature of our

Table 3. Distribution of Assortments and Sales Across Captaincy Arrangements

Captaincy arrangement	Average quarterly retail sales ($)	Average assortment size
Firm A–captain	597,330	55
Firm B–captain	546,805	58
Retailer	569,608	56

Table 4. Reduced Form Results—Linear Regression (OLS)

	Brand-level analysis			Manufacturer-level analysis		
Coefficients	Assortments	Average price	Market share	Assortments	Average price	Market share
Assortments	—	−0.00	0.02***	—	−0.00	0.01***
		(0.00)	(0.00)		(0.00)	(0.00)
Average price	−0.57*	—	0.00	−0.57*	—	−0.01
	(0.33)		(0.00)	(0.33)		(0.01)
Market share	0.47***	−2.13***	—	0.47***	−2.13***	—
	(0.03)	(0.22)		(0.03)	(0.22)	
Category captain	0.90**	0.33***	−0.03	2.12**	−0.03	−0.03
	(0.31)	(0.05)	(0.06)	(0.56)	(0.05)	(0.03)
Competitor price	—	0.53***	—	—	−0.27***	—
		(0.05)			(0.07)	
Average store space	−0.02	—	—	0.00	—	—
	(0.02)			(0.03)		
Total assortment	0.11***	—	—	0.30***	—	—
	(0.00)	—		(0.01)	—	
Brand dummies	Included	Included	Included			
Manufacturer dummies				Included	Included	Included
Region dummies	Included	Included	Included	Included	Included	Included
Time dummies	Included	Included	Included	Included	Included	Included
Constant	15.15	3.08***	0.19**	−2.66	9.46***	0.27***
	(1.01)	(0.36)	(0.07)	(2.77)	(0.49)	(0.01)
n = 1,094				n = 638		
Adjusted R^2	0.76	0.38	0.83	0.79	0.68	0.85

Notes. Data are aggregated to brand level across stores in each period. Category captain is a dummy variable indicating the captain's brands in captaincy managed retail chains. Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

data, we will not be able to reject this explanation. However, we have data on changes in captaincy arrangements for a few chains that we use to suggest that category captaincy arrangements could indeed lead to the effects we propose. In our data, only one chain switched from a no-CC arrangement to a CC arrangement, whereas, for two chains, the arrangement remained CC, but the identity of the captain changed. We employed a difference-in-difference (DiD) strategy to explore the impact of CC arrangements in these two scenarios. We treated the other chains in the metropolitan statistical area (MSA) that did not undergo the change as controls.

Table 6 and Table A.6 in Online Appendix A present the results in the scenario where the firm changed from a CC arrangement to a no-CC arrangement. First, at the chain level, most of the coefficients on CC are insignificant due to low power (only 14 data points). However, the coefficients are in the predicted direction. Both total assortment and total sales for the chain go up under the CC arrangement. Second, at the brand level, brand market shares and assortment of the captain's

Table 5. Distribution Across Captaincy Arrangements and Brands

	Captaincy arrangement			Captaincy arrangement			Captaincy arrangement		
	Market shares			Assortments			Average prices		
Manufacturer	Firm A–captain	Firm B–captain	Retailer	Firm A–captain	Firm B–captain	Retailer	Firm A–captain	Firm B–captain	Retailer
Firm A–brand 1	−0.09	0.02	0.12	0.06	−0.03	-0.08	−0.25	0.05	0.36
Firm A–brand 2	0.23	−0.36	−0.09	0.29	−0.49	−0.06	−0.00	0.15	−0.16
Firm B–brand 1	−0.16	0.10	0.18	−0.04	0.19	−0.10	−0.08	0.33	−0.15
Private label	−0.14	0.10	0.18	0.23	−0.23	−0.24	−0.27	0.84	−0.09
Others	0.14	−0.16	0.09	0.70	−0.25	−1.02	0.68	1.23	−1.26

Notes. Numerical values in the table represent the average z-values for each brand across arrangements. For instance, the first row suggests that firm A–brand 1 has the lowest market share under own captaincy (−0.09) and highest under retailer (0.12).

Table 6. Reduced Form Results—Brand-Level Analysis on Data from Regions with Change in Captaincy

Coefficients	Linear regression (OLS)					
	Scenario 1			Scenario 2		
Dependent variable →	Assortments	Average price ($)	Market share (s/s_0)	Assortments	Average price ($)	Market share (s/s_0)
Assortments	—	—	0.02***	—	—	0.02***
			(0.00)			(0.00)
Average price	—	—	−0.02*	—	—	−0.00
			(0.01)			(0.00)
Treated	−5.74**	0.34	0.12***	−0.44	−0.06	−0.01
	(1.90)	(0.26)	(0.02)	(0.52)	(0.01)	(0.02)
Treatment	0.16	−0.37	0.00	0.34	−0.04	0.00
	(0.27)	(0.28)	(0.02)	(0.58)	(0.01)	(0.02)
Captain's products	9.16*	0.54	0.17**	0.83	−0.29	−0.03**
	(4.79)	(0.66)	(0.06)	(0.83)	(0.22)	(0.01)
Captain's products × Treated × Treatment				1.67*	−0.20	0.05**
				(0.97)	(0.26)	(0.02)
Constant	10.57	5.81***	0.09	19.32***	6.39***	0.16
	(1.78)	(0.25)	(0.07)	(0.58)	(0.25)	(0.03)
Brand dummies				Included	Included	Included
Region dummies				Included	Included	Included
Time dummies				Included	Included	Included
n = 68				n = 515		
Adjusted R^2	0.10	0.02	0.79	0.72	0.20	0.84

Notes. Scenario 1: These are data from a single region with two chains. One chain (the treated) changed from captaincy-managed to retail-managed, whereas the other chain (the control) was always captaincy-managed. Treatment is the period under which the chain was captaincy-managed. *Captain's products* is a dummy variable obtained from the interaction of *Treated* × *Treatment* and captain's brands. Scenario 2: These are data from three regions, where two chains switched captaincy from one manufacturer to another. Both chains that switched (treated) changed from the same manufacturer to another. The other chains in the regions (control) are a mix of retailer-managed and captaincy-managed chains. Treatment is the period after the change. Two-way interactions were conducted but not reported. Data are aggregated to brand level across stores in each period. Standard errors are in parentheses.

***p < 0.01; **p < 0.05; *p < 0.1.

products are significantly higher under the CC arrangement than under the retailer arrangement. The impact of the CC arrangement on prices is positive but insignificant.

Table 6 presents the results from the scenario where the identity of the captain changed. Our theory has no prediction on chain-level differences in assortments and sales when the identity of the captain changes, so we restrict the analysis to brand-level differences in sales, assortment, and prices. First, we find that the total number of products of the captain's brand goes up when the switch happens. Second, the average price of the captain's brand goes down and the market share of the captain's brand goes up, but this is not significant.

Overall, our analyses show the effect of category captaincy arrangements on assortments, sales, and shares in our data. In particular, the results show evidence for the substitution and market-coverage effects. However, to measure the efficiency effect of captaincy and to understand the profitability and welfare implications of captaincy arrangements, one would need to know the marginal costs and fixed costs of carrying and planning different assortments. These costs are unobservable and can be recovered only through a structural model. Such a model also enables us to do counterfactual analysis, an important consideration given the sparseness of data wherein retailers switch captaincy arrangements.

3. Structural Model

Our structural model consists of four main components: (i) a demand submodel that specifies consumer preferences for products, (ii) a pricing submodel that specifies the vertical and horizontal interactions between manufacturers and retailers, (iii) an assortment submodel that captures the trade-off between the increased revenue from adding a product to the assortment and the increased cost of a bigger assortment, and (iv) a captaincy selection decision submodel that models the decision of a manufacturer and retailer to enter a captaincy arrangement.

The intuition of our model setup is as follows. Assortment selection depends upon demand factors (what a consumer does if a product of his choice is not available), the competitive landscape (the next best option), and costs (inventory, stocking, and replenishment costs).

These, in turn, depend on substitution patterns between products, vertical interactions between manufacturers and retailers, and horizontal interactions between manufacturers. When a product is not available on the shelf, a consumer is likely to either buy another product within the same category or go to another retail store to buy the same product. The retailer's incentive while choosing assortments is to minimize lost sales by choosing products that are easily substitutable. In addition, retailers gain due to upstream competition between manufacturers when the competing products are closer in product space. On the other hand, manufacturers prefer assortments where they are differentiated from other manufacturers. These differences in motivations lead to assortments and prices that differ between retailer and category captaincy arrangements.

Stages 0–3: Channel Decisions

There are four sets of decisions being modeled in this section: captaincy selection, assortments, wholesale price, and retail price. We model assortments and prices sequentially instead of simultaneously, because the assortment decision is stickier than the price decision. Note that the retail chain constitutes the natural level of analysis because a captain is appointed by the retailer for the entire chain. In each time period, the category decision maker chooses a subset of SKUs for the chain from the assortment superset for this market.[7] We assume that this superset is known and available to all actors. Notice that our superset assumption and assortment selection accommodates (i) variation in assortments within stores in a particular chain, and (ii) variation in SKUs offered by manufacturers across different markets, thereby allowing us to study the variation in assortments arising from captaincy versus retailer management arrangements. The sequence of decisions for the four-stage game played by the manufacturers and retailers in each quarter is as follows:

0. Retailers and manufacturers agree on the captaincy arrangement. No agreement is tantamount to retailer management of the category.
1. Category managers (either category captain or retailer) observe realizations of cost shocks that are unobserved by the econometrician; they simultaneously choose the assortment to carry and incur a fixed cost for each product carried.
2. For each SKU included in the assortment, manufacturers observe realizations of demand and marginal cost shocks that are unobserved by the econometrician; they choose wholesale prices simultaneously.
3. After observing the wholesale prices, the retailer chooses retail prices for all SKUs included in the assortment simultaneously.

Stage 0: Captaincy Selection

The expected profit for a retail chain from carrying a given assortment is the expected revenue from carrying that assortment net of the expected marginal cost of carrying the product. In addition, retail chains incur two different fixed costs: (a) a fixed cost for carrying products, consisting of electricity and stocking costs, and (b) a fixed cost for making the assortment decision, consisting of administrative and labor costs. Formally, let the expected profits for retailer k from assortment Ω_k from a superset of assortments Θ be defined as

$$\Pi_k(\Omega_k) = E[\pi_k|X_k, \Omega_k] - F_k, \tag{1}$$

where $E[\pi_k|X_k, \Omega_k]$ is the expected profit from carrying assortment Ω_k net of marginal costs. The expectation is taken over demand and cost shocks. For ease of notation, we define $\tilde{\pi} \equiv E[\pi|\ldots]$. The fixed costs incurred by the chain are denoted by F_k. In particular,

$$\begin{aligned} F_k &= F_{ak} + F_{pk} \quad \textit{where} \\ F_{ak} &= \sum_{j\in\Omega_k} C_j \\ F_{pk} &= f_k(X_k) + \zeta_k + \eta_{ak}, \end{aligned} \tag{2}$$

where F_{ak} is the fixed cost of carrying products and varies with assortment Ω_k chosen (C_j is the fixed cost of carrying per product). We allow C_j to vary based on store characteristics (store size), new products (to accommodate slotting fees), and captaincy arrangements. Further, F_{pk} is the fixed cost of making assortment decisions (planning and management costs) and consists of a fixed cost $f_k(X_k)$ that varies with chain characteristics X_k, a mean zero-error term ζ_k that also varies with chain, and a mean zero-error term η_{ak} that captures the effect of stocking and replenishment of products of different sizes and packaging on fixed costs. Note that η_{ak} varies by assortment chosen and chain but does not vary by product or across captaincy arrangements. This implies that both retailers and manufacturers will incur the same shock when choosing the same assortment combination for that chain. On the other hand, the assortment planning cost captures costs related to planning and management costs surrounding the assortment decision.

Retailers delegate assortment decisions to category captains. In return, captains incur the fixed cost of making assortment decisions (F_{pk}). Given the negotiation aspect surrounding the selection of category captaincy, we model the captaincy selection process on the contours of a simple game, wherein retailers delegate the assortment decision authority in exchange for a transfer of fixed costs associated with making assortment decisions. The contours of the game are as follows. The retailer decides to offer a captaincy arrangement sequentially to all manufacturers who offer her a higher profit. In other words, the retailer's profits under a captaincy arrangement with manufacturer m must be as high as under the retailer R managing the category herself. Manufacturers then decide on accepting captaincy or not. Manufacturer m will accept a captaincy arrangement only if the arrangement leaves him as well off as any other possible arrangement. If negotiations break down, then the retailer manages the category. We further assume that all actors (retailers and manufacturers) know the returns from various assortment choices under different arrangements only in expectation. Mathematically, this translates as follows.

For the retailer:

$$\int_{\eta}\left[\tilde{\pi}_k^{Cm} - F_{ak}\right]d\eta \geq \int_{\eta}\left[\tilde{\pi}_k^{R} - F_{ak}\right]d\eta - F_{pk}, \tag{3}$$

where $\tilde{\pi}_k^{Cm}$ is the expected profits for chain k under captaincy Cm management and $\tilde{\pi}_k^{R}$ is the expected profits for chain k under retailer management. Under a captaincy arrangement, the retailer does not incur the fixed cost of making assortment decisions (F_{pk}) but does incur the fixed cost of carrying products associated with the assortment F_{ak}. Note that $\tilde{\pi}(\cdot)$ is also an expectation but over marginal and demand cost shocks.

For manufacturers, the necessary condition translates to

$$\int_{\eta}\left[\tilde{\pi}_m^{Cm}\right]d\eta - F_{pk} \geq \min\left(\int_{\eta}\left[\tilde{\pi}_m^{R}\right]d\eta\,, \int_{\eta}\left[\tilde{\pi}_m^{C\tilde{m}}\right]d\eta\right), \tag{4}$$

where $\tilde{\pi}_m^{Cm}$ is the expected profits for manufacturer m under his captaincy Cm management and $\tilde{\pi}_m^{R}$ and $\tilde{\pi}_m^{C\tilde{m}}$ are the expected profits for manufacturer m under retailer management R and other manufacturers $C\tilde{m}$, respectively. Under captaincy, manufacturers incur additional costs but also the right to choose the assortments. As mentioned earlier, manufacturers can use this to make product decisions that strategically decrease competition between products. The concern, however, is that this can come at the expense of rivals, while not leading to any efficiency increases in the channel. We turn to the modeling of assortments under the different arrangements next.

Stage 1: Assortment Submodel: Category Captaincy

Category captaincy allows scope for opportunistic behavior by the category captain; in the extreme, a trivial equilibrium solution for the captain would be to stock only his own products and none belonging to his rivals. To avoid this trivial solution, we impose the constraint that once the captain is chosen, the retailer imposes the restriction that, in expectation, the retailer must make at least as much profit within the captaincy arrangement as she did under her management. In addition to this constraint, the category captain must consider the fact that introducing products with similar characteristics will reduce markups due to more intensive cross-substitution. This will push the category captain toward introducing products that are differentiated from one another. This consideration, along with the constraint imposed by the retailer, prevents the category captain from dropping a rival's product if he does not have a close substitute for it. It is important to note that our assortment model does not consider the constraint of limited shelf space. We implicitly assume that changes in assortment will affect the number of facings allocated to each product in the assortment and that the shelf space allocated to each product is not directly influenced by the captain.

The category captain m chooses an assortment $\Omega_k \subset \Theta$ after observing shocks η_{ak} based on the following expected profit function:

$$\Pi_m^{Cm}(\Omega_k) = \tilde{\pi}_m^{Cm}(\Omega_k) - F_{pk} \tag{5}$$

subject to the constraint that $\tilde{\pi}_k^{Cm} - F_{ak} \geq \int_{\eta}[\tilde{\pi}_k^{R} - F_{ak}]d\eta$.

The expectation for both retailers and manufacturers is over the distribution of cost ϕ and demand shocks ξ, which we define as Ξ. We assume that both retailers and manufacturers have the same information on the distribution of these shocks. We denote by $\tilde{\pi}_m^{Cm}(\Omega_k)$ the expected profit to the manufacturer from choosing assortment Ω_k and by $\tilde{\pi}_k^{Cm}(\Omega_k)$ the expected profit to the retailer from the manufacturer choosing assortment Ω_k. Note also that F_{pk} is the fixed cost of making assortment decisions and $\int_{\eta}[\tilde{\pi}_k^{R} - F_{ak}]d\eta \equiv E\Pi_k^{R}$ is the expected profit that the retailer makes from retailer management. It is important to note that the retailer incurs the fixed cost of carrying the product under both category captaincy and under retailer management. This is a stronger condition than Equation (3) and states that, in addition to incurring the fixed cost of assortment planning, the retailer expects her net profits under captaincy to be at least as high as when she was managing the category. The constraint imposed by the retailer is "soft," in that it allows the category captain to add or drop any product to the assortment, but at a cost. The form of the soft constraint is similar to that used in Besanko and Doraszelski (2004), Snider (2009), and Besanko et al. (2010). The cost of the constraint is

$$F_{cc}(\Omega_k) = \left(\frac{\tau}{1+\nu}\right)\left(\frac{E\Pi_k^{R}}{\Pi_k^{Cm}}\right)^{\nu}\left(\left|E\Pi_k^{R} - \Pi_k^{Cm}\right|\right), \tag{6}$$

where $\nu \geq 0$ measures the hardness of the capacity constraints and $\Pi_k^{Cm} = \tilde{\pi}_k^{Cm} - F_{ak}$. As $\nu \to \infty$, $(\frac{E\Pi_k^{R}}{\Pi_k^{Cm}}) \to 0$ if $\Pi_k^{Cm} > E\Pi_k^{R}$ or is equal to ∞ if $\Pi_k^{Cm} > E\Pi_k^{R}$. Finally, τ captures the effect of this constraint. Rewriting the category captain's expected profits using the "soft" constraints gives

$$\Pi_m^{Cm}(\Omega_k) = \tilde{\pi}_m^{Cm}(\Omega_k) - F_{pk} - F_{cc}(\Omega_k). \tag{7}$$

A category captain offers the assortment that maximizes his expected profit function; that is,

$$\Pi_m^{Cm}(\Omega_k|\Xi) > \Pi_m^{Cm}\big(\Omega_k'|\Xi)\big) \ \forall\ \Omega_k' \subset \Theta_k. \tag{8}$$

We use the above equation to obtain the moment inequalities that are used in our estimation.

Stage 1: Assortment Submodel: Retailer Management

In the retailer management condition, retailers incur the fixed cost of carrying a product as well as the fixed cost of making assortment planning decisions. The retailer therefore will introduce products until the expected profit from expanding the assortment is less than the fixed cost of product addition. Note that, unlike under captaincy, introducing products with similar characteristics does not necessarily reduce markups for the retailer. This is because, whereas a captain's incentives are to pick assortments that differentiate his products from his rival manufacturers, the retailer cares only about preventing substitution to the outside good.

The retailer chooses an assortment $\Omega_k \subset \Theta_k$ based on the following profit function:

$$\Pi_k^R(\Omega_k) = \tilde{\pi}_k^R(\Omega_k) - F_{pk} - F_{ak}. \tag{9}$$

Again, the expectation is over the distribution of demand shocks ξ and cost shocks ϵ, and $\tilde{\pi}_k^R(\Omega_k)$ is the expected profit to the retailer from choosing assortment Ω_k.

The optimal assortment decision for the retailer is obtained by maximizing the profit function; that is,

$$\Pi_k^R(\Omega_k|\Xi) > \Pi_k^R\big(\Omega_k'|\Xi)\big) \ \forall\ \Omega_k' \subset \Theta_k. \tag{10}$$

Similar to the category captain scenario, we use the above equation to obtain moment inequalities that are used in our estimation framework.

Once the assortment decision is made, manufacturers and retailers observe demand and cost shocks, after which wholesale and retail prices are chosen.

Stage 2: Wholesale Prices

Manufacturers choose prices to maximize profits. The profit function for each manufacturer m in chain k at time t is given by

$$\pi_k^m(p_t^m) = \sum_{j\in\Phi_{mk}} \left[p_{jk}^m - c_{jk}^m\right] s_{jk}\left(p_{jk}^k\left(p_{jk}^m\right)\right) - C_k^m, \tag{11}$$

where $\Phi_{mk} \subset \Omega_k$ is the set of all products that manufacturer m sells to retailer k, c_{jk}^m is the marginal cost for manufacturer m to produce product j, p_{jk}^k is the retail price when manufacturer m charges wholesale price p_{jk}^m, $s_{jk}(\cdot)$ is the market share for product j, and C_k^m is the fixed cost incurred by the manufacturer to serve a particular chain. The FOCs for the manufacturer are given by

$$p_k^m - c_k^m = -\left[T_m \times \Delta_k^m\right]^{-1} s_k^k(p). \tag{12}$$

Note that $T_m(i,j) = 1$ if manufacturer m owns both products i and j, and is zero otherwise, and that Δ_k^m is the demand response to wholesale price as in Villas-Boas (2007), given by $\Delta_k^m(j,l) = \frac{\partial s_{jk}(p_{jk}^k)}{\partial p_{lk}^m}$.

Stage 3: Retail Prices

Retailers choose prices to maximize category profits, which are given by

$$\pi_k\big(p^k, p^m|\xi, \epsilon, X, \theta\big) = \sum_{j_k\in\Omega_k} \left[p_{jk}^k - p_{jk}^m - c_{jk}^k\right] s_{jk}\left(p_{jk}^k\right) - C_k^k, \tag{13}$$

where p_{jk}^k is the price charged by retailer k for product j, p_{jk}^m is the wholesale price charged by the manufacturer to the retail chain k for product j as a function of all prices in the time period, and C_k^k includes all retail fixed costs that do not change with time, such as electricity and marketing costs. The objective function for the retailer is therefore given by

$$p^{k*} = argmax\ \pi_k\big(p^k, p^m\big), \tag{14}$$

where p^{k*} is a vector of optimal prices charged by the retailer. The first-order conditions (FOCs) are

$$s_{lk}(p_{lk}^k) + \sum_{j_k\in\Omega_k} \left[p_{jk}^k - p_{jk}^m - c_{jk}^k\right] \frac{\partial s_{jk}\left(p_{jk}^k\right)}{\partial p_{jk}^k} = 0. \tag{15}$$

Written in matrix form, the price-cost margins are

$$\begin{pmatrix} \vdots \\ P_t^k \\ \vdots \end{pmatrix} - \begin{pmatrix} \vdots \\ P_t^m \\ \vdots \end{pmatrix} - \begin{pmatrix} \vdots \\ Mc_t^k \\ \vdots \end{pmatrix} = -\begin{pmatrix} \ddots & \vdots & \ddots \\ \dots & T_k \times \Delta_t^k & \dots \\ \ddots & \vdots & \ddots \end{pmatrix}^{-1} \begin{pmatrix} \vdots \\ S_t^k \\ \vdots \end{pmatrix}, \tag{16}$$

where P_t^k is a vector of all retail prices at time t and P_t^m is the vector of all wholesale prices charged by manufacturers to retailers; Mc_t^k is the vector of marginal costs for products at time t; T_k is a matrix indicating the ownership structure, that is, $T_k(i,j) = 1$ if the retailer maximizes profits for product i, j and zero otherwise; Δ_t^k is a matrix of own and cross-price elasticities and is given by $\Delta_t^k(j,l) = \frac{\partial s_{jt}(p_{jt}^k)}{\partial p_{lt}^k}$; and S_t^k is a vector of market shares for all products. Rewriting Equation (16), we get

$$P_t^k - P_t^m - Mc_t^k = -\left[T_k \times \Delta_t^k\right]^{-1} S_t^k. \tag{17}$$

Stage 4: Consumer Demand Submodel

We model demand using a discrete choice random coefficient model of consumer utility as described by Berry et al. (1995), hereafter referred to as BLP. The BLP specification accommodates differences in consumer preferences for individual products within a category while simultaneously controlling for the endogeneity of prices. The demand estimation is at the chain-market level.[8] A product in this context is defined as an SKU in the category. A set $\Omega_{krt} \subset \Theta_{krt}$ of products is available to every chain k in region[9] r at time t, where Θ_{krt} is the superset of all products that is available in time period t. Each individual consumer i chooses a product $j_{krt} \in \Omega_{krt}$ in every time period t or chooses the outside option. Every product offered in time period t consists of attributes $(X_{jkrt}, \xi_{jkrt}, p_{jkrt})$. The vector X_{jkrt} includes (i) product characteristics that do not vary over time, (ii) brand fixed effects, and (iii) seasonal effects; ξ_{jkrt} are product characteristics that are observable to the consumer but unobservable to the econometrician (e.g., shelf space), and p_{jkrt} denotes the price for product j at time t for chain k in region r. With this notation and standard application of the BLP, the model-predicted share of product $j \in \Omega_k$ is given by

$$\begin{aligned} s_{jk}(x, p, \delta, \lambda) &= \int \frac{\exp\left[\delta_{jk} + \mu_{ijk}(x_{jk}, p_{jk}, \lambda_i, D_i)\right]}{1 + \sum_{m \in \Omega_k} \exp\left[\delta_{mk} + \mu_{imk}(x_{mk}, p_{mk}, \lambda_i, D_i)\right]} \\ &\quad \times dF_{D,\lambda}(D_i, \lambda_i), \end{aligned} \tag{18}$$

where δ_{jk}, equal to $p_{jk}\alpha + X_{jk}\beta + \xi_{jk}$, captures mean effects and is known as the *linear* part of the utility function (Nevo 2000b). Further, $\mu_{ijk} \equiv -\lambda_{ijk}p_{jk} - \Pi D_i p_{jk} + \epsilon_{ijk}$ captures effects that vary by individual and is referred to as the *nonlinear* part of the utility (Nevo 2000b), and $F_{D,\lambda}(D_i, \lambda_i)$ is the joint distribution of λ_i, D_i (see Online Appendix B for further details on how we arrived at this final specification).

4. Estimation Strategy

We need to estimate the demand parameters $\theta^d = (\alpha_i, \beta)$, the marginal cost parameters γ, and the fixed cost parameters (F_{pk}, F_{ak}). The estimation strategy consists of two steps: (i) estimating the demand and marginal cost parameters θ^d and γ to obtain estimates of profits conditional on observed assortment choices, and (ii) estimating bounds on the fixed cost parameters using the estimates from the previous step. The following sections describe the estimation strategy in detail. With respect to the model mentioned in the previous section, parameters from stages 2–4 are estimated in the first step and parameters in stages 0 and 1 are estimated in the second step.

Demand and Marginal Costs

Following recent literature (Villas-Boas 2007, Chen et al. 2008), we estimate demand and supply sequentially using a generalized method of moments (GMM) estimation procedure. On the demand side, we use the BLP procedure to obtain the means and standard deviations of the coefficients of price, brand, and other variables in the random coefficient logit model. Briefly, we first solve for the mean utility numerically using a contraction mapping. This yields a linear equation relating mean utility to the product preference dummies, prices, and other exogenous variables. As pointed out in the literature, the prices set by firms are likely to depend on unobserved product attributes (ξ_{jt} in the demand model), which means that price is effectively an endogenous variable, and we need to instrument for it to obtain consistent estimates. The standard BLP approach involves an instrumental variables (IV) regression, with the residuals from the regression used as the residuals in a GMM estimation, as described below.

On the supply side, the specification of a Bertrand–Nash pricing game by the retailer leads to a certain implied price-cost margin, which can be calculated once we have estimates of the demand-side parameters in place. Briefly, the Bertrand–Nash pricing game assumes that firms compete in prices, as opposed to quantities. According to this model, situations with differentiated products will lead to equilibrium prices that are a function of both marginal costs and a positive markup term that reflects demand for the products. We combine this calculation of the price-cost margin under the assumption of a Stackelberg game[10] between the retailer and manufacturers to back out wholesale prices and manufacturer costs.

We assume that the retailer incurs no additional marginal costs beyond the wholesale price paid to the manufacturer. This is reasonable in the DSD system that is present in our context, because manufacturers deliver, place their SKUs on the retailer's shelf, and rotate stock at no cost to the retailer, regardless of category captaincy status. Hence, the retailer's main expenditure in this frozen food category is electricity, which is largely fixed given the size of the freezer cases and does not vary by the number of SKUs sold; consequently, it drops out of the FOC equation. We then regress these marginal costs on a set of cost characteristics. Formally, we assume that the marginal cost for a product j at time t is

$$c_{jt}^{m} = \gamma X_{jt}^{k} + \phi_{jt}, \tag{19}$$

where X_{jt}^{k} is a vector of cost characteristics, γ is the vector of coefficients that affect costs, and ϕ_{jt} is the portion of costs unobserved by the econometrician. The cost equation captures the costs of transportation, delivery, and offering different product attributes. Denoting the price-cost margin as PCM_{jt}, we obtain the estimated pricing equation as

$$p_{jt}^{k} - PCM_{jt}^{m} - PCM_{jt}^{k} = \gamma X_{j}^{k} + \phi_{jt}. \tag{20}$$

We assume a constant elasticity of marginal cost for every attribute. Although restrictive, this is a justifiable cost function to use, given our lack of information on issues such as economies of scale. The parameters are estimated as in Villas-Boas (2007). At this stage of the estimation, we obtain the demand parameters $\theta^{d} = (\alpha_i, \beta)$, cost parameters γ, and the distribution of demand and cost shocks Ξ.

4.1. Fixed Costs—Carrying Costs

To estimate the fixed cost for including an SKU in an assortment, we use the moment inequalities estimator developed in Pakes et al. (2015). This method uses a "revealed preference" approach to recover the parameter values. In other words, we use the assumption that profits from the observed assortment are greater than the profits from alternative assortments that were not offered. Notice that these are the necessary conditions for a Nash equilibrium in this context. For example, consider the case of including a product in the assortment. If the product was included in the assortment, then it must have been the case that the profits from not adding the product was less than the profits from adding the product. Similarly, if the product was not included in the assortment, then it must have been the case that the profits from adding the product were lower than the profits of not adding it. These necessary conditions allow us to construct the requisite inequalities.

We derive inequalities for every chain's assortment choice in a particular region at a particular time period. The objective function varies depending on whether a category captain arrangement exists or not. The first inequality is obtained by adding a product to the assortment. This generates a lower bound for the product. Similarly, the upper bound is generated by dropping the product from the assortment.

4.1.1. Inequalities Estimator.

Recall that the category captain chooses assortment $\Omega_k \subset \Theta_k$ based on the following profit function:

$$\Pi_{m}^{Cm}(\Omega_k) = \tilde{\pi}_{m}^{Cm}(\Omega_k) - F_{pk} - F_{cc}(\Omega_k), \tag{21}$$

where $\tilde{\pi}_{m}^{Cm}(\Omega_k)$ is the expected profit to the captain from choosing assortment Ω_k, F_{pk} is the fixed cost of assortment planning incurred by the captain to make the assortment planning decision, and $F_{cc}(\Omega_k)$ is the "soft" penalty imposed by the retailer's constraint.

To specify the inequalities estimator, we need to predict the expected profits $\tilde{\pi}_{m}^{Cm}(\cdot)$ and "soft" penalty $F_{cc}(\cdot)$ for both the observed and alternate assortments.

We use the demand and marginal cost estimates to predict the profits for an assortment in each chain in a particular time period t; that is,

$$\hat{\pi}_{jt}^{Cm}\left(\Omega_{kt}|\theta, \gamma, \xi_{jt}, \phi_{jt}\right) \equiv \sum_{\Omega_{kt}} \left(\hat{p}_{jt}^{Cm} - \hat{c}_{jt}^{w}\right)\hat{s}_{jt}M, \tag{22}$$

where $[\hat{\cdot}]$ represent estimated values. The expected profit $\tilde{\pi}_{m}^{Cm}(\cdot)$ is obtained by recalculating $\hat{\pi}_{jt}^{Cm}$ over the distribution of demand shocks ξ and cost shocks ϕ. To do this, we bootstrap 100 times over the predicted values of $\hat{\xi}, \hat{\gamma}$ and recalculate the new equilibrium prices and market shares over the new distribution. The expected profit is the average over these bootstraps. In calculating expected profits in this manner, we assume that the demand and marginal cost shocks are independent and identically distributed over all products in a particular chain in a particular time period. This is true for both products that are currently in the assortment and those that are not a part of the assortment. Other alternative distributional assumptions on simulating the error distributions, such as using brand specific shocks or product specific shocks, yield similar results to our current distributional assumption.

Although obtaining $\tilde{\pi}_{m}^{Cm}(\cdot)$ is time-consuming but computationally straightforward, obtaining $F_{cc}(\cdot)$ is far more challenging. To understand the challenges involved, recall that

$$F_{cc}(\Omega_k) = \left(\frac{\tau}{1+\nu}\right)\left(\frac{E\Pi_{k}^{R}}{\Pi_{k}^{Cm}}\right)^{\nu}\left(\left|E\Pi_{k}^{R} - \Pi_{k}^{Cm}\right|\right),$$

where $\Pi_{k}^{Cm} \equiv \tilde{\pi}_{k}^{Cm} - F_{ak}$ is the profit that the retailer k expects to make from the captaincy arrangement with manufacturer m and $E\Pi_{k}^{R} \equiv \int_{\eta}[\tilde{\pi}_{k}^{R} - F_{ak}]d\eta$. Calculating this constraint requires us to identify the assortments that would have been chosen under alternate arrangements under different fixed cost shocks. Whereas we observe the assortments and subsequent profits under the current arrangement, we do not observe the optimal assortment and profits under alternate arrangements. To calculate profits under the alternate arrangements, we need to know (a) the optimal assortment that would be offered under each alternate arrangement, and (b) the fixed carrying costs of products. Each of these is a challenge. Calculating the optimal assortment is a combinatorially hard problem (classified as NP-hard). For example, calculating the optimal assortment and subsequent profits for a category with an assortment superset of 72 SKUs (the average in our data) requires us to enumerate 2^{72} combinations and then simulate each one of these assortment combinations over 100 draws for each one of these assortment combinations. To get a sense of the time that this calculation would take, note that obtaining the optimal profits for one assortment combination over 100 simulation draws takes five minutes running parallel on a computer with eight processors. Calculating the optimal assortment for just this one market would thus take 4.5e16 years (4.72e21 × 5 minutes). As for fixed carrying costs, those are unobservable at this stage, which means that it is impossible to provide a stopping rule to the assortment optimization problem.

In view of these challenges, we make two assumptions to address the problem of calculating the profits under alternate arrangements. First, we assume that manufacturers (as captains) and retailers choose from the realized set of assortment choices, rather than from all possible assortment choices. To obtain the realized set of assortment choices, we first consider the current assortments observed across the retail chains in the data. Call this set A. We then form another set, consisting of assortments obtained by adding or dropping a product from the current assortment of each retail chain. Call this set B. Our final set of all possible assortments is the union of the two sets, A and B. Second, we assume that carrying cost shocks are drawn from a type II error distribution (logit). The two assumptions together, although restrictive, allow us to proceed without the need for a stopping rule.[11] We conducted a few robustness checks around these assumptions by increasing the assortment sets that were considered (e.g., allowing all assortment sets seen in the data and considering some assortment sets that were not observed but could potentially be possible) and find results to be very similar across different assumptions.

The expected profit for the retailer from retailer management is now given by the familiar logsum logit expression

$$E\Pi_k^R = \log\left(\sum_{\Omega_k \in \bar{\Theta}} \exp\left(\tilde{\pi}_k^R - \sum_{j \in \Omega_k} C_j\right)\right). \tag{23}$$

It is important to note that, in Equation (23), one still needs to simulate over the marginal costs and demand shocks Ξ to obtain $\tilde{\pi}_k^R$, and the fixed cost C_j is unobservable and needs to be estimated.

To generate the moment inequalities, consider the case where an SKU is added to the assortment. According to our earlier discussion, the expected profits from the current assortment should be greater than the expected profits from any other assortment that can be formed by adding any product from the superset. This implies that

$$\Pi_m^{Cm}(\Omega_k|\Xi) \geq \Pi_m^{Cm}(\Omega_{k+1}|\Xi), \tag{24}$$

where $\Pi_m^{Cm}(\Omega_{k+1})$ is the profit function obtained from adding a product from assortment Ω_k in chain k. The expectation is taken conditional on I_k, the chain information set at the time when the category captain makes his choice. This generates the following inequality:

$$E\left\{\triangle\hat{\tilde{\pi}}_m^{Cm}\left(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt}\right) - \triangle F_{cc}|I_k\right\} + \triangle\eta_k \geq 0, \tag{25}$$

where the difference function $\triangle F_{cc} \equiv F_{cc}(\Omega_k) - F_{cc}(\Omega_k + 1)$. Similarly, $\triangle\hat{\tilde{\pi}}_m^{Cm}(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt})$ is the difference function obtained by differencing the expected profits between current and alternate assortment combinations. To obtain the expectation, we add every product that is not in the assortment Ω_k, but belongs to the superset of products available to the chain Θ_k, to the current assortment and recompute the profits from the new assortment Ω_{k+1}. The upper bound is obtained in a similar way by dropping every product from the assortment one at a time and recomputing expected profits from the new assortment Ω_{k-1}.

We generate moment inequalities for chains managed by retailers in a similar fashion. The lower bound for adding a product under retailer management is given by

$$E\left\{\triangle\hat{\tilde{\pi}}_k^R\left(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt}\right) - \triangle C(X_k) + \triangle\eta_k|I_k\right\} \geq 0, \tag{26}$$

where $\triangle C(X_k, \delta) \equiv C_j(X_k)$ is the fixed cost of carrying a product in the assortment, which varies based on store characteristics (store size), new products (to accommodate slotting fees), and captaincy arrangement. Similarly, $\triangle\hat{\tilde{\pi}}_k^R(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt})$ is the difference function obtained by differencing the expected profits between current and alternate arrangements.

We generate moments for all the chains and regions, leading to 203 moments. Applying a similar methodology to "dropping" a product from the assortment generates an additional 203 moments.

4.2. Fixed Costs—Assortment Planning

To estimate the fixed cost for assortment planning, we use a similar strategy as before to generate moment inequalities. In particular, we use the necessary conditions implied by the game in stage 0 to recover the parameter values.

For the retailer,

$$\int_\eta [\tilde{\pi}_k^{Cm} - F_{ak}]d\eta \geq \int_\eta [\tilde{\pi}_k^R - F_{ak}]d\eta - F_{pk}, \quad (27)$$

and for manufacturers,

$$\int_\eta [\tilde{\pi}_m^{Cm}]d\eta - F_{pk} \geq \min\left(\int_\eta [\tilde{\pi}_m^R]d\eta\, , \int_\eta [\tilde{\pi}_m^{C\tilde{m}}]d\eta\right). \quad (28)$$

As before, we have the problem of identifying assortments that would have been chosen under alternate arrangements, under the different fixed cost shocks mentioned earlier. We maintain the assumptions made earlier: (i) we assume that possible assortment choices are restricted to the assortment plans currently realized in the market, and (ii) we assume that η follows a type II error (logit) distribution. With these assumptions, the necessary conditions translate into

$$E\Pi_k^{Cm} \geq E\Pi_k^R - F_{pk} \quad (29)$$

for the retailer and

$$E\Pi_m^{Cm} - F_{pk} \geq \min\left(E\Pi_m^R, E\Pi_m^{C\tilde{m}}\right) \quad (30)$$

for the manufacturer, where

$$E\Pi_m^R = \sum_{\Omega_k \in \tilde{\Theta}} \Pr(\Omega_k)_m^m \left[\tilde{\pi}_m^R - \sum_{j \in \Omega_k} C_j\right], \quad (31)$$

$$E\Pi_m^{C\tilde{m}} = \sum_{\Omega_k \in \tilde{\Theta}} \Pr(\Omega_k)_m^m [\tilde{\pi}_m^{C\tilde{m}}], \quad (32)$$

$$E\Pi_m^{Cm} = \log\left(\sum_{\Omega_k \in \tilde{\Theta}} \exp(\tilde{\pi}_m^{Cm})\right). \quad (33)$$

Note that the necessary conditions for the manufacturer (Equation (28)) provide the upper bound for the fixed cost of assortment planning, whereas the necessary conditions for the retailer (Equation (27)) provide us with the corresponding lower bound. The resulting inequalities are as follows:

$$E\{\triangle E\hat{\Pi}_m - F_{pk} + \zeta_k | I_k\} \geq 0, \quad (34)$$

$$E\{\triangle E\hat{\Pi}_k + F_{pk} - \zeta_k | I_k\} \geq 0, \quad (35)$$

where $\triangle E\hat{\Pi}_m$ is the difference in expected profits for the manufacturer between being a captain and not being a captain. Similarly, $\triangle E\hat{\Pi}_k$ is the difference in expected profits for the retailer from the captaincy arrangement compared with all other arrangements.

It is important to note that we cannot estimate assortment planning costs that vary by manufacturer. In order to do so, we require separate upper and lower bounds on these costs for each manufacturer and retailer. Consider the information on captaincy arrangements that we have in our data. We observe chains with and without captaincy arrangements; the former is needed to calculate the upper bound on assortment planning costs for a manufacturer, whereas the latter is needed to calculate the lower bound. Given the information we have, there is no problem with calculating manufacturer-specific upper bounds. However, the lack of a captaincy arrangement, by itself, is not enough to calculate individual lower bounds; we also need to know *why* captaincy did not happen. Sticking to the reasonable assumption that a necessary condition for a retailer and a manufacturer to agree on captaincy is that both of them should make at least as much profit under captaincy as under other possible arrangements, a lack of agreement on captaincy could be because (a) the retailer's profits under captaincy were not high enough, (b) the manufacturer's profits under captaincy were not high enough, or (c) neither's profits were high enough. We have no additional information that helps us pick one of these conditions; short of making a heroic assumption that lets us arbitrarily pick an alternative, we cannot use the condition of noncaptaincy to draw inferences necessary to obtaining a manufacturer-specific lower bound.

Stacking the $1 \ldots J$ moments together gives us the following equation for estimation:

$$P_J m(z, \theta) = \frac{1}{J}\sum_j \begin{bmatrix} E\left\{\triangle\hat{\tilde{\pi}}_m^{Cm}\left(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt}\right) - \triangle F_{cc} + \triangle\eta_k\right\} \\ E\left\{\triangle\hat{\tilde{\pi}}_k^{R}\left(\Omega_k|\theta, \gamma, \xi_{jt}, \phi_{jt}\right) - \triangle C(X_k) + \triangle\eta_k\right\} \\ E\left\{\triangle E\hat{\Pi}_m - F_{pk} + \zeta_k\right\} \\ E\left\{\triangle E\hat{\Pi}_k + F_{pk} - \zeta_k\right\} \end{bmatrix} \geq 0. \quad (36)$$

The identified set of parameter values is the set that satisfies the implied system of inequalities:

$$\Theta_j = argmin_{\theta \in \Theta} \|(P_J m(z, \theta))_-\|, \quad (37)$$

where $(\cdot)_- = \min\{\cdot, 0\}$. In our estimation, we use a procedure similar to that followed by Pakes et al. (2015) to recover the set estimates for X_k, F_{pk}, τ, and standard errors.

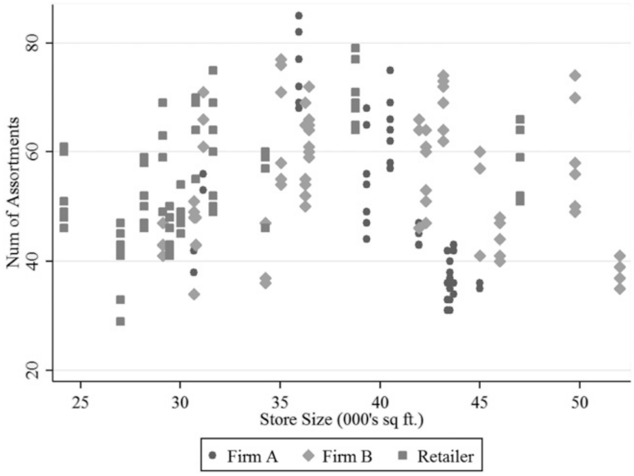
4.2.1. Instruments. Recall that the term ξ in the demand model represents unobserved demand shocks. It is highly likely that these time-varying shocks are correlated with the chosen prices, thus creating a potential endogeneity bias. We instrument for the price of a product to control for this endogeneity. Following Hausman (1996) and Nevo (2001), we use prices of the product in other regions and raw material costs as instruments. The assumption we make here is that, after controlling for brand-specific means and demographics, region-specific shocks are independent across regions (but are allowed to be correlated within regions). The prices of product j in two regions will be correlated due to the common marginal cost but will be uncorrelated with market-specific demand shocks due to the independence assumption. Specifically, for the price of a given product j in chain k at time t, we use the average price across other regions for that product for that time.

4.3. Identification

Our identification strategy builds on features in our data. We have already shown a number of tables that show directional support for our hypotheses (e.g., between revenues, assortment share, assortment size, prices, and category arrangements; see Tables 2–6). In particular, consider the variation shown in Figure 1. Observe that similar-sized retail chains, within the same geographical area and time period, have larger assortments when managed by captains than when managed by retailers. This variation helps us identify the fixed costs of carrying and assortment planning; in other words, we infer the fixed costs of captaincy by looking at the variation that occurs when chains with different captaincy arrangements, facing a similar superset of products, choose different assortment combinations. This variation is observed both between retailers (cross-sectional) and within retailers (temporal). Formally, the identifying assumption in our structural model is that, after conditioning on observables, the impact of captaincy is only through assortments (both number and the products carried).

The marginal cost parameters are identified from the assumptions on the pricing game combined with the demand parameters. Finally, the variation in prices and product attributes identifies the demand parameters.

Figure 1. Distribution of Assortment Size by Store Size and Captaincy



Note. This figure shows the distribution of assortment sizes across different store sizes by captaincy arrangement (legend).

5. Results

5.1. Demand Estimates

We ran the demand model separately for the eight markets, both for computational ease and to allow preferences to vary flexibly across markets. We show the results from one market, Baltimore. Table C.9 in Online Appendix C contains descriptions of the variables used in the demand estimation. Table C.10 in Online Appendix C reports three different specifications: a simple logit specification, which involves an OLS regression with the difference between log(share) of each of the inside goods and the outside good (i.e., $\ln(\frac{s_j}{s_0})$) as the dependent variable, with no instruments for price and no control for unobserved heterogeneity; a logit estimation with instruments for price but no control for unobserved heterogeneity (denoted logit+IV); and a random coefficient logit model with instruments for price and controls for unobserved heterogeneity (denoted RC logit+IV). We find that accounting for price endogeneity and heterogeneity makes a significant difference—the mean price sensitivity under OLS is −0.34, which is closer to zero than the random coefficient estimate of −1.02. The downward bias toward zero presents evidence for price endogeneity. However, it is important to note that heterogeneity plays a more important role in our context than endogeneity. This is similar to Rossi (2014), who suggests that endogeneity is less of a concern in retail data after sufficient controls have been added. Moving from the logit IV model to the random coefficient logit model increases price sensitivity significantly. We focus on the random coefficient logit estimates in what follows.

The mean price coefficient is significantly negative (−1.02). Heterogeneity and demographic factors have a significant impact on price sensitivity. In general, households with children are more price sensitive (0.75). Although not reported here for brevity, we find that preferences across the eight markets are broadly similar, directionally.

5.2. Cost Estimates

Table C.19 in Online Appendix C shows the results for the cost regression from Equation (19). First, note that the cost estimates seem to satisfy face validity, in that SKUs with multiple ingredients are more expensive to produce. Second, there is heterogeneity across firms in production costs. Our estimates imply an average cost of \$3.49 for producing an SKU. The implied wholesale and retail margins are in the range of \$1.10–\$2.00. These were confirmed to be reasonably accurate by the managers of the firm we worked with on this study.

Table 7 describes the results from the inequalities estimation. The specification for the fixed cost of carrying an SKU in the assortment consists of the following variables: a constant, number of new products carried, average store size,[12] a dummy variable for category captaincy, and the interaction of category captaincy with average store size.[13]

Our set estimates for the impact of category captaincy on fixed costs are negative and significant. The set estimates of the category captaincy–store size interaction are also negative and significant. The overall impact of captaincy on fixed costs for each chain is obtained by adding the set estimates of captaincy with the set estimates of category captaincy–store size interaction. This impact is negative for all chains; the impact on the chain with the smallest store size (25,000 square feet) in our data set is −$75. These results suggest that the fixed costs of adding an SKU are lower under category captaincy than under retailer management. The set estimates on average store size are positive and significant, suggesting that the fixed costs of carrying are higher for larger stores. The set estimate on the number of new products carried is negative, significant, and small, suggesting that the additional cost of carrying new products for the store is very low.

The fixed assortment planning cost for a chain with 27 (the median number of stores per chain per MSA in our data) stores in the region is around $4,600 per quarter. This represents the amount that any manufacturer would be willing to pay for captaincy. The finding that fixed costs under category captaincy are lower implies that manufacturers acting as captains are more efficient at making assortment decisions than are retailers. This finding is in line with industry observers (e.g., Desrochers et al. 2003) who contend that manufacturers are specialists in their particular categories, whereas retailers must contend with many different categories. To put these results into perspective, absent category captaincy, the average fixed cost of adding an SKU to the assortment in a chain with store size of 30,000 square feet (the average store size in our data) is $370 per chain per quarter. With category captaincy, these costs are substantially lower (around $292). This result provides evidence for our efficiency effect. Note that we cannot provide evidence for our market coverage or substitution effects yet, as these require a comparison of captaincy and retailer management arrangements. This can be done only through a counterfactual analysis, which is what we turn to in the next section.

6. Counterfactuals

Our goal is to analyze the impact of category captaincy on producers and consumers using our structural model estimates. In order to compute the changes resulting from an observed retailer management setting to a counterfactual category captaincy setting, we have to identify the optimal assortment and prices that would be selected in the alternate arrangement. Because our estimation did not specify an assortment selection algorithm, in order to compute a counterfactual scenario, we have to enumerate all possible combinations to arrive at the optimal assortment. This is computationally intensive; for example, even without considering substitution effects, computing the optimal assortment from a superset of 50 SKUs requires us to enumerate $2^{50} - 1$ combinations. Consequently, we utilize a heuristic approach to assortment selection that uses greedy and interchange heuristics (Fisher and Vaidyanathan 2014). These authors report that the heuristic generates solutions that are 98.5% optimal. Having identified the optimal assortment with this procedure, we add or drop SKUs individually to this set, recalculating the equilibrium in each instance to obtain the optimal assortment set. Computationally, the steps in our calculations are as follows.

Optimal Assortments

1. Identify an assortment combination using the Fisher–Vaidyanathan procedure.

a. Greedy heuristic: Add SKUs in decreasing order of revenue contribution until revenues exceed cost.

Table 7. Inequalities Analysis Results

Variable	Coefficient	95% Confidence interval
Fixed cost – Carrying costs		
Per SKU:		
Constant	940	[885, 994]
Number of new products	−0.09	[−0.34, −0.09]
Average store size (square feet in thousands)	−19	[−27, −17]
Category captain	−67	[−90, −65]
Category Captain × *Average store size*	−0.35	[−0.17, −0.51]
Fixed cost – Planning costs		
Constant	−260	[−580, −106]
Number of stores	180	[100, 259]

Notes. Coefficients represent predicted costs to store per product (SKU). *Category captain* is an indicator variable for when the store is managed by category captains. The average store size in our data set was around 36,000 square feet, and the median number of stores per chain per MSA was 27.

b. Interchange heuristic: Start with a given assortment and test whether interchanging an SKU that is not in the assortment increases profits. Revenue-increasing interchanges are made when discovered. The process continues until a full run over all possible interchanges identifies no revenue increasing interchange.

2. With the assortment identified above:

a. Simulate demand and cost shocks for the assortment.

b. Predict demand and cost residuals for the assortment.

c. Compute optimal retail and wholesale prices.

d. Compute the profit function given cost parameters and computed optimal prices

e. Repeat the process for 100 realizations of demand and cost shocks to compute average profits for the assortment.

3. Add or drop an SKU to this assortment until all the combinations are exhausted.

4. The assortment with the highest profit is the optimal assortment.

We computed two counterfactual scenarios with data from two chains. In the first scenario, we evaluate the consequences of a change from retailer management of category to manufacturers managing the category. In the second scenario, we evaluate a policy change where category captaincy is banned. It is important to note that, since we have endogenized the selection of category captaincy, both of our scenarios are off-equilibrium predictions, that is, would never occur absent any exogenous change in factors. For instance, in the first scenario where we evaluate the consequence of change from retailer management (existing scenario) to manufacturer management of the category, we find no situation where the profits to a manufacturer were positive after incorporating the retailer's penalty constraint. This suggests that manufacturers would never be category captains in equilibrium. We therefore exogenously change the retailer's penalty constraint to be the current profits of the retailer (as opposed to expected profits). Similarly, in the second scenario, we evaluate retailer management of the category knowing fully well that category captaincy by firm A (the bigger manufacturer) is the preferred arrangement.

In the first scenario, we evaluate three cases: the base case where the retailer manages the category, and the second and third cases where firm A and firm B are the captains, respectively. Note that firm B has a smaller set of SKUs in the base assortment than does firm A. In the second scenario, we evaluate two cases, the base case where firm A (the bigger manufacturer) is the captain, and the second case where the retailer manages the category. The results from the counterfactuals are detailed in Table 8. We discuss these results below.

6.1. Assortment Size and Composition Effects

First, relative to retailer management, assortment size increases under captaincy under all conditions. To use our typology, there is evidence of a market coverage effect, but it varies depending on the characteristics of the appointed captain. This is due to a combination of two factors—the lower costs of managing assortments under captaincy and the constraint imposed by the retailer. Absent the retailer's constraint, the appointed captain would have excluded all of the rival's SKUs. To understand assortment expansion, note that carrying each SKU from a rival provides no revenues from that SKU to the captain and also decreases his profits due to increased competition between his SKUs and the rival's SKU. Given that firm B has fewer SKUs in the base case than does firm A, the former faces a greater hurdle in expanding the assortment. Firm A, on the other hand, is able to meet the retailer's constraint with just its own products.

There is also evidence for the substitution effect—the captain favors his own SKUs when he modifies the assortment. Both captains behave similarly in this respect and swap out rivals' SKUs. Intuitively, captains should swap out slow-moving SKUs, a conjecture confirmed by our counterfactuals.

6.2. Price and Market Share Effects

Tables D.1 and D.2 in Online Appendix D show the detailed impact of different arrangements on assortments and prices. Under category captaincy, the impact on retail prices is a mixed bag. Prices of firm A's products go down under firm A's captaincy, whereas prices of firm B's products go up (by a very small amount) under firm B's captaincy. These findings match the patterns observed in our descriptive statistics. Prices of the rival's SKUs go down. Likewise, market shares of the rival's SKUs go down, whereas those of the captain go up. Most of these changes in prices and market shares are traceable to the addition/deletion of SKUs.

The business significance of these effects is better seen by considering the implied revenue shifts. The impact of captaincy on retailer profits is positive. The retailer's net profits increase by around 1.2% with firm B as the captain and by 8.2% (in scenario 1) and 18.4% (in scenario 2) when firm A is the captain. The benefits to the retailer occur due to both the transfer of assortment planning costs to the retailer and the increase in revenues from the larger assortment.

In contrast, category captaincy's impact on manufacturers varies depending on whether firm A or firm B is the captain. In scenario 1, when appointed as captain, firm A gains 23%, but firm B (with fewer SKUs) loses 4.5%. It is important to note that these revenues are net of assortment planning costs. Thus, whereas firm B sees an increase in revenues under

Table 8. Counterfactual Analysis for Baltimore Market

	Chain 1			Chain 2	
	Category arrangement			Category arrangement	
	Retailer	Firm B – captain	Firm A – captain	Firm A – aptain	Retailer
		Number of SKUs		Number of SKUs	
Assortment superset	78	78	78	78	78
Assortment carried	32	38	35	41	38
		Profits ($)		Profits ($)	
Retailer	91,090	92,254	98,790	47,821	40,362
Firm A	120,500	101,620	148,280	9,528	9,600
Firm B	12,217	11,669	10,768	39,512	36,872
Producer surplus	223,807	205,543	257,838	96,861	86,834
		Consumer surplus		Consumer surplus	
Consumer surplus (δ_+)		90,700	−122,000		156.4
Consumer surplus (δ_-)		−12,500	4,215		−0.05

Notes. Chain 1: The analysis was done on data from a chain which originally had 47 products. The average store space for this store was 30,000 square feet. The table shows the results from counterfactual analysis of three scenarios: (a) when the retailer is managing the category; (b) when firm A is managing the category; and (c) when firm B is managing the category. Chain 2: The analysis was done on data from a chain which originally had 47 products. The average store space for this store was 42,000 square feet. The table shows the results from counterfactual analysis of two scenarios: (a) when firm A is managing the category and (b) when the retailer is managing the category.

its captaincy, it sees an overall decline after accounting for assortment planning costs it now incurs as captain. Under the rival's captaincy, firm A (with more SKUs) loses around 15%, whereas firm B loses around 11%. We can look closer at the change in assortment by computing clout and vulnerability numbers for each of the manufacturers. These are shown in Tables D.1 and D.2 in Online Appendix D. We find that captaincy lets a manufacturer differentiate himself more effectively from other manufacturers, via a judicious selection of the product assortment. This is observed most clearly when the small manufacturer, firm B, is the captain. Firm B, as the smaller manufacturer, has the strongest incentive to differentiate himself from firm A. Observe that when firm B is the captain, vulnerability goes down, for the products of *both* firm A and firm B. This suggests that products are maximally differentiated under firm B's captaincy. On the other hand, when firm A is the captain, clout for both firms' products go up, but vulnerability is unchanged. This is because, as the dominant player in the market, firm A is unable to reduce competition within its own products (intrabrand competition).

6.3. Welfare Effects

Channel profits, defined as the sum of retailer and manufacturer profits, increase under firm A (15% in scenario 1 and 11% in scenario 2). On the other hand, channel profits decrease under firm B (−8%). It is important to note that, in equilibrium, firm B will never be the captain, as the retailer and firm A make more profits with firm A as the captain. The increase in channel profits largely comes from a reduction in the fixed costs (around 65%), and the rest from an increase in revenues. Turning to consumer surplus, following convention, we calculate it based on compensating variation as $CW_t = \sum_{i=1}^{ns} \frac{\log(\sum_{j=1}^{J} \exp(\delta_j - \alpha_i p_j))}{\alpha_i}$. The results are reported based on their effect on two sets of consumers. The first, δ_+, is the impact on consumers who gained positive utility under the different scenarios. A positive value suggests a gain in consumer surplus due to the change. Similarly, δ_- captures the impact of counterfactual scenarios on consumers who experience a negative utility. A negative value here suggests a gain in consumer surplus. From Table 8, we see that category captaincy increases consumer surplus when firm B is the captain but not when firm A is the captain. In scenario 2 (Table 8), there is a small increase in consumer surplus when captaincy is banned. We provide more discussion on the implications of consumer welfare on policy in the section below.

7. Discussion and Implications

Category captaincy has attracted the attention of both industry observers and policy makers, but there is little consensus about its presumptive effects, as witnessed by the divergent commentaries on the landmark *Conwood Co. v. United States Tobacco. Co.* case which held a captain guilty of monopolization (see review by Klein and Wright 2004). We attempted to examine these effects empirically, by specifying and estimating a model of category captaincy. We had framed the effects of captaincy in the form of a series of questions that concerned (i) the overall size of product assortments; (ii) the composition of the assortment, that is, whether it favored the captain; (iii) the impact on retail prices;

and (iv) the overall impact on consumer welfare and firm profits. We had further delineated our understanding of the impacts of captaincy in terms of three effects: an *efficiency effect* that occurs if the shift to captaincy lowers the upfront fixed cost per period; a *market-coverage effect* due to the addition of SKUs that a retailer would have otherwise not carried; and a *substitution effect* due to a rival manufacturer's SKUs being dropped from the assortment carried. The discussion that follows discusses the outcomes of captaincy in terms of the three effects just mentioned.

First, we find evidence for all three effects. Captaincy seems to be efficiency-enhancing, in terms of reducing channel costs, which go down fairly dramatically. This is reasonable—we had speculated earlier that a major reason for captaincy would be the manufacturer's comparative advantage in a particular category, and that seems to be the case. Somewhat less intuitive is the impact of captaincy on the number and type of products that get sold. We find that the absolute number of SKUs in the category increases, suggesting greater market coverage; this is accompanied, however, by a decrease in the number of products from rival manufacturers (i.e., not the captain). This substitution effect implies that captaincy is indeed advantageous to the captain and is consequently something manufacturers would seek to attain.

Looking at outcomes such as prices and profits, we find that average prices increase slightly, as do channel profits. The conclusion on price increases has to be tempered with the realization that the assortments are different; in that sense, a comparison between retailer management and captaincy is not very meaningful. As for profits, although the increase in channel profits is further evidence of enhanced efficiency, it is important to recognize that each actor is affected differently. Whereas the retailer and the captain increase their profits, the rival manufacturer sees a decline in some circumstances. (Clearly, if we had the additional constraint that all manufacturers had to agree to any one of them being a captain, the likelihood of a successful captaincy agreement would decrease considerably.) Finally, and somewhat nonintuitively, consumer welfare goes up under captaincy. This result tells us how important it is to analyze nonprice service elements to gain a fuller picture of captaincy; the addition of more SKUs and a different assortment composition proves to be surplus-enhancing for both retailers and consumers.

Implications for Policy

There is a striking contrast between horizontal antitrust issues (e.g., a horizontal merger of erstwhile competitors) and vertical antitrust issues (e.g., vertical contracts between an upstream producer and a downstream producer). The Department of Justice's horizontal merger guidelines of 2010 provide definitive advice about the theoretical background and evidentiary standards by which horizontal antitrust issues are to be assessed; a similar consensus exists in academic scholarship on the subject, with Nevo (2000a) being an illustration of the "gold standard" for this type of structural analysis.

In contrast to this state of affairs, vertical antitrust issues are best described as contested terrain. The 1984 Department of Justice Vertical Merger Guidelines have been formally rescinded but never replaced; in effect, there is no formal guidance at present. This lenient policy view has come under criticism from both academics and policy scholars. Perhaps the most comprehensive critique is offered by Khan (2016). She argues that the current emphasis on short-term price changes to compute consumer welfare effects is misplaced and overlooks possible negative nonprice effects. There are analytical models suggesting nonprice effects of vertical arrangements, including exclusive dealing, foreclosure, and raising rivals' costs (see Comanor and Rey 2000). However, practically all the empirical research on vertical issues (see Brenkers and Verboven 2006, Chen et al. 2008, Asker 2016), work only through price changes.

To the best of our knowledge, the current work is one of the few structural analyses of nonprice effects (assortments) of a vertical arrangement. Our immediate results disclose that category captaincy reduces costs, specifically the cost of assortments, and thus increases the size of assortments. Increased variety is presumptively procompetitive, but the net effects are more complex because final prices also increase, on average. On net, recall that consumer welfare increased when the nondominant producer was the captain and decreased when the dominant producer was the captain. This framework sets out a firmer footing for formulating policies than the ad hoc evidentiary search for "bad acts" that often characterizes litigation absent a theoretical model.

In sum, category captaincy arrangements should be judged by a rule of reason standard, and the magnitude of effects are driven by the size and composition of assortment changes and price changes. Absent a large-scale removal of rivals' SKUs (i.e., a large-scale substitution effect), we can expect consumers to be better off. Our counterfactual analysis highlights the important role of the retailer in policing category captaincy, as illustrated in the Conwood litigation.

More generally, beyond captaincy arrangements, our work sets out a policy-friendly methodology to incorporate nonprice effects; we endogenize assortment decisions into a structural analysis of welfare effects of vertical contracts. Our approach can be folded into analyses of other vertical arrangements, for example, the structural analysis of the effects of a direct-to-store (DSD) channel versus a wholesaler channel by Chen et al. (2008).

Implications for Practice

Turning to the managerial implications of our work, category captaincy is not a profit-improving move for all the channel actors. The retailer always wins, as does the larger firm when it is appointed as the captain. On the other hand, a smaller manufacturer loses revenues for the retailer and is ineffective when appointed as the captain (channel profits go down). Thus, manufacturers have an incentive to be appointed as the captain when a move to category captaincy is contemplated by the retailer; captaincy improves profits, or at least holds down losses from a manufacturer's perspective. If a firm is unable to be appointed as a captain, our results show that it would be advised to focus its efforts on further differentiating its SKU assortment from that of the captain.

Limitations

Our work is but a first step in incorporating prices and assortments into the empirical study of category captaincy arrangements. As noted earlier, an important limitation of our empirical exercise is the modeling of category captain selection. Ideally, one would model this selection process and use variation in data that independently affects the retailer's incentives. We do not have data with such variation, which precludes the obvious approach just outlined. Instead, we model the incentives of the retailer and the manufacturer to enter into a captaincy arrangement. Even this requires major assumptions, such as a restriction on the set of possible retail assortments and on the distribution of profits. Although we do examine these assumptions for their robustness, it is fair to acknowledge that their use suggests caution in applying our conclusions to other contexts where the assumptions may not hold.

Two directions for future work suggest themselves immediately. First, most obviously, one can investigate better ways of incorporating captaincy selection without imposing the restrictive assumptions we make in the paper. A possibility is to conceive of a richer bargaining model of captaincy selection that allows transfer amounts to vary between manufacturers. A second avenue for progress involves setting up a more elaborate model of captaincy wherein the captain explicitly controls other aspects of the marketing mix, such as promotions, shelf space, and stocking.

Acknowledgments

The authors thank Mauricio Varela, Mark Bergen, Amil Petrin, Kyoo Il Kim, Minjung Park, and Suman Basuroy for helpful advice. In addition, the authors thank seminar participants at the Carlson School of Management; University of Toronto; McGill University; University of Western Ontario; University of California, Los Angeles; University of Arizona; University of Rochester; Penn State University; and University of Iowa for their helpful comments and Noah Houg for help during data collection. The data for this study were generously provided by a national food manufacturer and AC Neilsen. The research was graciously supported by the Institute for Research in Marketing, Carlson School of Management.

Endnotes

[1] In an antitrust case, *Conwood Co. v. United States Tobacco Co. 290 F3d 768 (6th Cir 2002), cert denied, 537 US 1148 (2003)*, the Supreme Court held that United States Tobacco *abused* its category captaincy status in the chewing tobacco category and awarded $1.06 billion in damages, one of the largest verdicts in antitrust history.

[2] A sparseness reflected in a Federal Trade Commission (FTC) chaired academic panel's appeal for further empirical evidence and fact-based research on the topic (Herderschee-Hunter 2003).

[3] To see why, consider that a category on average includes around 50 items in a store. Picking the optimal assortment from 50 products entails a calculation over $2^{50} - 1$ combinations, an infeasibly large number.

[4] Note that the frozen food category is particularly appropriate for a study that focuses on assortments. This is because direct-store-delivery (DSD) distribution systems are the norm in this category, and in the DSD system, the assortment decision is the primary one for the category captain (stocking and shelf-space management are largely done by each individual manufacturer for his own product).

[5] Our nondisclosure agreement with the firm that provided us the data prevents us from providing any information that would reveal the firm's identity. We have therefore substituted generic descriptors for the category, brands, and product features.

[6] In addition, we conduct a set of simultaneous equation models (3SLS) that account for the simultaneity of assortment, SKU average price, and market share. The analysis and corresponding results are presented in online Appendix A.

[7] Recall that this superset is the union of all SKUs stocked across all the chains in a market.

[8] In line with other work that examines chain/brand-level effects (Chen et al. 2008), we restrict demand to the chain level.

[9] We use the terms *region* and *geographic markets* interchangeably throughout this paper.

[10] Also known as a leader-follower game in which the leader firm (manufacturer in our case) moves first and then the follower firm (retailer in our case) follows sequentially.

[11] The assumptions, although allowing us to proceed, still require considerable amounts of computational time. We have around 28 markets for each of the eight geographical areas; the computation time required for one market is 2.5 hours. This leads to an overall estimation time of 523 hours (28 assortment combinations × 28 markets × 8 geographies × 5 minutes) for calculating the expected profits under the counterfactual arrangements.

[12] Store space is our proxy for store size. In general, bigger stores carry bigger assortments, whereas smaller stores carry smaller assortments. This measure is used to capture this fact.

[13] Recall that the penalty function applies only in instances where category captain arrangements are present and is given by $F_{cc}(\Omega_k) = (\frac{\tau}{1+\nu})(\frac{E\Pi_k^{Cm'}}{E\Pi_k^{Cm}})^{\nu}(|E\Pi_k^{Cm'} - E\Pi_k^{Cm}|)$. The parameters τ, ν are scaling parameters and are not identified. We normalize $\tau = 1$. A higher value of ν implies a harder constraint. We assumed that this constraint is satisfied in equilibrium and calculated the values of ν0000 that support that assumption. Any value of $\nu > 5$ satisfied the assumption. We conducted robustness checks at different values of ν and obtained broadly similar results.

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