Yasin Alan, Jeffrey P. Dotson, & Mümin Kurtuluş

On the Competitive and Collaborative Implications of Category Captainship

Category captainship (CC) is a retailing practice wherein a retailer collaborates with one of the manufacturers in a product category (referred to as the captain) to develop and implement a category management strategy. Although CC has been studied using both theoretical models and surveys, empirical evidence on the benefits and drawbacks of CC is scarce. The authors use a unique data set collected during a CC implementation to empirically examine the impact of CC on the retailer, the captain, and the other manufacturers in the category. The authors find that both the retailer's private label and the captain benefit from CC because of pricing and assortment changes. They also find that some competing manufacturers benefit from CC while others suffer. Specifically, the manufacturers that closely compete with the captain benefit, whereas the manufacturers that are in close competition with the private label suffer because the retailer protects its private label. The authors show that category sales would have been higher if the retailer had not protected its private label. This study sheds light on how joint consideration of assortment and pricing, the presence of a private label, and product characteristics may influence the outcomes of CC implementations.

Keywords: category management, category captainship, private label, retailing, channel partnerships

Online Supplement: http://dx.doi.org/10.1509/jm.15.0196

Category management is a commonly used retailing practice in which a retailer treats a product category (i.e., a set of similar products) as a strategic business unit. A product category (e.g., canned vegetables, salty snacks, carbonated beverages) consists of products offered by national brands and may also include private label products offered by the retailer. Category management enables retailers to focus on maximizing category performance, typically measured by the sales or profitability of the entire category, instead of making decisions on a product-by-product basis (Zenor 1994). Prior research in marketing has shown that category management can be beneficial for retailers because it enables them to simplify, coordinate, and thereby improve the process of making assortment, pricing, and other merchandising decisions (ACNielsen 2005; Basuroy, Mantrala, and Walters 2001; Dhar, Hoch, and Kumar 2001).

Effective category management requires a retailer to align its product offerings with evolving consumer needs. Because retailers manage many categories, constant monitoring and interpretation of consumer trends is a costly and labor-intensive task for them. Manufacturers typically have a better understanding of consumer needs because their expertise is focused on a much smaller set of products and categories (Blattberg and Fox 1995). The combination of retailers' lack of resources and manufacturers' superior category knowledge creates supply chain collaboration opportunities. Accordingly, many retailers manage some of their categories in collaboration with one of their leading manufacturers. These leading manufacturers are often referred to as category captains, and the practice itself is referred to as category captainship (CC; Desrochers, Gundlach, and Foer 2003; Federal Trade Commission 2001, 2003).

Category captainship has become a preferred way of executing category management. General Mills, for example, assisted one retailer in the dry packaged dinners category by replacing slow-moving stockkeeping units with faster-turning products (*Progressive Grocer* 2011). Abbott Nutrition helped a retailer in the baby food and consumables category by recommending a new planogram with some new products in the assortment and changing prices to reflect the new product mix (*Progressive Grocer* 2010). In addition, J.M. Smucker Co. helped several retailers in the canned and packaged beverages category by developing new shelf concepts and endcap displays based on consumer insights (*Progressive Grocer* 2015). In summary, the captain's recommendations vary across retailers and categories and may affect assortment, pricing, and/or merchandising decisions.

The trade literature has suggested that both retailers and manufacturers can benefit from CC (e.g., *Progressive Grocer* 2010, 2011, 2015). However, controversies regarding CC have arisen because the captain provides recommendations to the retailer regarding not only its own products but also those of its competitors. Consequently, the captain may have a positive bias toward its own products to the detriment of the competitors' products. The term "competitive exclusion" has often been used

Yasin Alan is Assistant Professor of Operations Management, Owen Graduate School of Management, Vanderbilt University (e-mail: yasin.alan@owen.vanderbilt.edu). Jeffrey P. Dotson is Associate Professor of Marketing and Global Supply Chain, Marriott School of Management, Brigham Young University (e-mail: jeff.dotson@byu.edu). Mümin Kurtuluş is Associate Professor of Operations Management, Owen Graduate School of Management, Vanderbilt University (e-mail: mumin.kurtulus@owen.vanderbilt.edu). The authors thank the *JM* review team for valuable feedback that greatly helped improve the quality of this article. Kusum Ailawadi served as area editor for this article.

ISSN: 0022-2429 (print)
1547-7185 (electronic)

Journal of Marketing
Vol. 81 (July 2017), 127–143
DOI: 10.1509/jm.15.0196

to refer to situations in which the captain uses its position to put its competitors at a disadvantage (Carameli 2004; Federal Trade Commission 2003).

The existing research on CC is based on legal theory (e.g., Wright 2009); surveys (Gooner, Morgan, and Perreault 2011; Morgan, Kaleka, and Gooner 2007); game theoretic models of retailer–manufacturer interactions under CC (e.g., Kurtuluş and Nakkas 2011; Kurtuluş, Nakkas, and Ülkü 2014; Subramanian et al. 2010); and structural estimation, which enables counterfactual analyses regarding how a hypothetical CC implementation would have affected category decisions and performance (Nijs, Misra, and Hansen 2014). However, empirical evidence on the collaborative and competitive implications of CC is scarce, as retailers are reluctant to share CC data because of antitrust concerns (Nijs, Misra, and Hansen 2014). From a collaborative standpoint, the existing literature on CC does not provide a formal analysis of an actual CC implementation to assess whether and how CC benefits the retailer and the captain. From a competitive standpoint, there is no empirical evidence regarding whether CC benefits or hurts the competing manufacturers. Accordingly, our goal in this article is to empirically study the implications of CC for the retailer, captain, and competing manufacturers using a unique data set collected during a CC implementation.

Our data set contains 52 weeks of product-level measures for all products in a shelf-stable food category with significant private label presence. During this time period, the retailer conducted a full category review in collaboration with one of the largest manufacturers in the category. Because the retailer treated this category as a revenue generator, the category review mainly focused on potential ways to increase category sales revenue. Recommendations generated during this review led to a new assortment and pricing strategy, which was implemented in week 21. By comparing sales revenue during the pre- and post-CC implementation periods (i.e., the first 20 weeks and the last 32 weeks in the data), we investigate the following research questions:

1. Does the retailer benefit from CC? If it does, are the benefits driven by pricing or assortment changes? Are there any other drivers beyond assortment and pricing?
2. What is the impact of CC on different manufacturers in the category, including the private label and captain? Is it possible for the competing manufacturers (i.e., all manufacturers except the private label and captain) to benefit from CC?
3. What determines whether a competing manufacturer benefits or suffers from CC?

Previous literature has raised similar questions (e.g., Ailawadi et al. 2010), but data-driven answers are not readily available. Addressing these questions through actual CC implementation data has several advantages over prior research on CC. First, the literature on CC considers pricing and assortment in isolation. For instance, Kurtuluş and Nakkas (2011) and Kurtuluş et al. (2014) focus on how CC influences a retailer's assortment, whereas Kurtuluş and Toktay (2011) and Nijs, Misra, and Hansen (2014) study how CC affects prices for a given assortment. While the existing models cannot fully capture the CC phenomenon because of their focus on only one possible lever, our study is unique in jointly considering pricing and assortment.

Second, many retailers view the private label as a key component of a successful category strategy (Kumar and Steenkamp 2007). Accordingly, retailers often use private label performance as one of the metrics to evaluate category performance (ACNielsen 2005, Chapter 6). Despite its practical relevance and importance, the impact of CC on private label products has not been considered in the existing CC literature. Our study shows how private label presence may affect category decisions and performance in the CC context.

Third, the assortment literature in marketing has shown that products with similar attributes (e.g., same size) are more likely to compete for demand (e.g., Rooderkerk, Van Heerde, and Bijmolt 2011, 2013). Following this literature, we specify an attribute-based demand model, whereas the existing CC literature has used more stylized models (e.g., linear demand model). Our study sheds light on how a product's similarity to the captain's products and private label products may affect whether such a product benefits or suffers from CC.

In summary, while our empirical findings are based on one CC implementation, our contribution stems from examining several factors that have not been considered in the CC literature. In particular, our study informs practitioners and researchers by demonstrating how joint consideration of assortment and pricing, the presence of a private label, and product characteristics may influence the outcomes of CC implementations.

The rest of this article is organized as follows. First, we summarize the relevant research and build a conceptual framework. We then describe our data set and empirical model. Next, we present our findings regarding the impact of CC. Finally, we conclude with a summary of our results and their implications as well as a discussion of the limitations of our study.

Theoretical Background and Conceptual Framework

In this section, we first provide a theoretical background for our study by reviewing previous research on pricing, assortment, and merchandising in the context of category management. Because these literature streams are vast, we limit our attention to studies that are most relevant to our setting. We then use this theoretical background to develop our conceptual framework.

Theoretical Background

Retail pricing under category management. Shifting from brand-centric management of retail prices to jointly setting prices in an entire category can lead to a significant improvement in category performance (e.g., Basuroy, Mantrala, and Walters 2001; Zenor 1994). Nonetheless, several factors make pricing a challenging task for retailers in the CC context. First, retailers should pay attention to cross-price effects because sales of a product depend on not only its own price but also the prices of substitute products in the category (e.g., Besanko, Dubé, and Gupta 2005; Kadiyali, Chintagunta, and Vilcassim 2000). Second, pricing decisions are influenced by the strategic role of the category (e.g., sales or profit maximization) for the retailer (ACNielsen 2005, p. 115). For instance, Zenor (1994) and Basuroy, Mantrala, and Walters (2001) show that implementing category management to maximize category profits can lead to higher retail prices compared with a brand-centric management of retail prices. In contrast, Dhar, Hoch, and Kumar (2001) show that best-performing retailers in terms of category sales are the ones with the lowest retail prices.

Third, the presence of a private label program is a key driver of a retailer's pricing decisions (Chintagunta, Bonfrer, and Song 2002). Many retailers give preferential treatment to private label products (Kumar and Steenkamp 2007) because they typically have higher percentage margins (Ailawadi and Harlam 2004), increase a retailer's bargaining power relative to national brands (Chintagunta, Bonfrer, and Song 2002; Pauwels and Srinivasan 2004), and can improve store loyalty in the case of high-quality private label products (Corstjens and Lal 2000). Such a preferential treatment affects retail prices. For instance, Chintagunta (2002) shows that the retailer's desire to increase private label market share drives the retail prices of private label products below the levels obtained under a category profit-maximization objective. In addition, private label introduction may decrease the retail prices of the national brands in the category (e.g., Chintagunta, Bonfrer, and Song 2002; Du, Lee, and Staelin 2005).

Despite increasing a retailer's bargaining power, increased private label presence may not necessarily increase store traffic or revenues (Pauwels and Srinivasan 2004) and may lead to lower dollar margins per unit (Ailawadi and Harlam 2004). Moreover, pushing private labels too far may hurt store loyalty as a result of an inverted U-shaped relationship between a household's private label share and store loyalty (Ailawadi, Pauwels, and Steenkamp 2008). In summary, private label presence exacerbates the difficulty of a retailer's pricing decisions because it requires the retailer to retain a balance between private label and national brands.

Finally, transitioning from traditional category management, in which the retailer makes decisions on its own, to CC can influence prices. The research studying this transition has modeled CC as an alliance between the retailer and the captain in settings in which the retailer tries to maximize category profits (Kurtuluş and Toktay 2011; Nijs, Misra, and Hansen 2014). These studies predict steep price decreases for the captain's products because the formation of an alliance between the retailer and the captain mitigates double marginalization, which enables the retailer to offer the captain's products at significantly lower prices. The competing manufacturers, in contrast, continue to suffer from double marginalization and make relatively minor price reductions as a response to the downward price pressure exerted by the captain (Kurtuluş and Toktay 2011; Nijs, Misra, and Hansen 2014). That is, the captainship literature has suggested that CC leads to a decline in retail prices, with the steepest price declines for the captain's products.

Assortment planning under category management. Finding the right assortment is a challenging task because most categories have tens or even hundreds of products, which makes it difficult for retailers to determine the right assortment size and composition. There is mixed evidence regarding the relationship between assortment size and category performance. On the one hand, a broader assortment is associated with higher sales (e.g., Borle et al. 2005; Dhar, Hoch, and Kumar 2001) because a large assortment makes it more likely for consumers to find a product that matches their needs (Boatwright and Nunes 2001). On the other hand, reducing assortment size by removing low-selling products has no or positive impact on category sales in some settings (e.g., Broniarczyk, Hoyer, and McAlister 1998; Drèze, Hoch, and Purk 1994). This is because consumer choice is affected by consumers' perception of variety, which is determined not only by the assortment size but also by other factors, such as the availability of consumers' favorite products (Broniarczyk, Hoyer, and McAlister 1998) and the number of brands in the category (Briesch, Chintagunta, and Fox 2009). Consequently, retailers struggle in aligning their assortments with consumer needs.

Even for a fixed assortment size, finding the right assortment composition is nontrivial because products within a category can cannibalize one another's sales. The complexity of assortment decisions has been tackled by attribute-based models that parsimoniously capture the interactions among many products. Fader and Hardie (1996) have developed a consumer choice model that characterizes each product by its attributes (e.g., brand, size, color). Subsequent research has shown that products with similar attributes (e.g., same size) are more likely to compete for demand within a category (Rooderkerk, Van Heerde, and Bijmolt 2011). Consequently, attribute-based models have been used to make assortment decisions (e.g., Rooderkerk, Van Heerde, and Bijmolt 2013).

Although the assortment research in the context of category management has focused on the retailer's assortment decisions, several articles have studied assortment decisions in the context of CC. For instance, Kurtuluş and Nakkas (2011) show that CC leads to higher category sales because the captain's consumer insights enable the retailer to offer an assortment that is better aligned with consumer needs. Furthermore, the captain can increase its own sales through excluding some competing brands from the category so that consumers switch to the captain's products (Kurtuluş and Nakkas, 2011; Kurtuluş et al. 2014). While CC benefits the retailer and the captain, it may hurt or benefit competing manufacturers. On the one hand, CC can lead to a decline in the shelf space allocated to competing manufacturers (Kurtuluş and Toktay 2011) or the captain may recommend removing a competitor's product from the assortment (Kurtuluş et al. 2014). On the other hand, CC is beneficial for competing manufacturers' products introduced to the assortment on a CC implementation (Kurtuluş and Nakkas 2011; Kurtuluş et al. 2014). Overall, the CC literature suggests that both the captain and the retailer benefit, whereas the competing manufacturers may benefit or suffer after CC is implemented.

Merchandising under category management. Although our data set does not have any variables associated with merchandising, we briefly discuss merchandising efforts in the context of CC to provide a more comprehensive theoretical background for our study. In practice, the captain's merchandising efforts focus mainly on providing the retailer with demand-enhancing services, such as shelf design, shelf-space allocation, and design of endcap displays (Subramanian et al. 2010, p. 1741). The literature has provided support for the benefits of such demand-enhancing services. For instance, a product's sales can improve by increasing the number of shelf facings allocated to that product (e.g., Chandon et al. 2009) and changing its shelf placement (e.g., Atalay, Bodur, and Rasolofoarison 2012; Drèze, Hoch, and Purk 1994). Moreover, taking into the account the decision sequence consumers follow to narrow down options (e.g., first flavor, then size) in organizing shelf displays (Nowlis, Dhar, and Simonson 2010) and designing shelves and aisles to increase the proximity of complementary products can improve category performance (e.g., Bezawada et al. 2009; Drèze, Hoch, and Purk 1994).

The CC literature has also considered the benefits of demand-enhancing efforts. In particular, Subramanian et al. (2010) focus on the impact of the captain's demand-enhancing services on category stakeholders. They suggest that such services benefit the retailer by improving category performance but may benefit or hurt the competing manufacturers depending on whether they increase overall category demand or shift demand from one brand to another. Similarly, Kurtuluş, Nakkas, and Ülkü (2014) consider CC in a context in which the total category demand is a function of the effort that the retailer or the captain exerts into demand-enhancing services. In their setting, the competing manufacturers benefit (suffer) from the captain's merchandising efforts if the captain keeps them in (removes them from) the assortment. In summary, the CC literature has documented that CC can improve category performance through the captain's merchandising efforts, and such efforts might benefit or hurt competing manufacturers.

Conceptual Framework

Our theoretical discussion reveals that the key drivers of category decisions in our context are (1) category objective, (2) private label presence, (3) collaboration with a captain, (4) cross-price and cross-assortment effects, and (5) attribute-based substitution among products. Drawing on these drivers, we have developed a conceptual framework (see Figure 1).

In light of the main objective of the CC implementation we study (i.e., improving category sales), our framework links CC to sales. This is aligned with practice, in which assessing category performance through sales (rather than profitability) is common in the CC context.[1] Although profit maximization may be a better goal for the retailer in some categories, asking the captain to improve profitability would require the retailer to share the competing manufacturers' proprietary information (e.g., wholesale prices) with the captain. However, legal authorities discourage retailers from sharing one manufacturer's proprietary information with another (Desrochers, Gundlach, and Foer 2003; Federal Trade Commission 2001). As a result, many retailers define category objectives in terms of sales in CC implementations (Kurtuluş, Nakkas, and Ülkü 2014; Kurtuluş et al. 2014).

Our framework posits that the captain might influence sales by making pricing, assortment, and/or merchandising recommendations. Moreover, manufacturer type (i.e., private label, captain, and competing manufacturers) and product attributes might moderate these recommendations and their impact on sales. In particular, manufacturer type determines the extent to which a manufacturer has control over category decisions, and product attributes determine substitution patterns within a category.

Impact of CC on retail prices. Our theoretical discussion suggests that implementing CC creates an alliance between the retailer and the captain, which in turn enables the retailer to lower retail prices for the captain's products. It also reveals that the retailer may choose to lower retail prices for private label products to boost private label sales. Combining these observations with the notion that the CC implementation we study attempts to increase category sales, we expect that CC will reduce retail prices for the captain's and private label products.

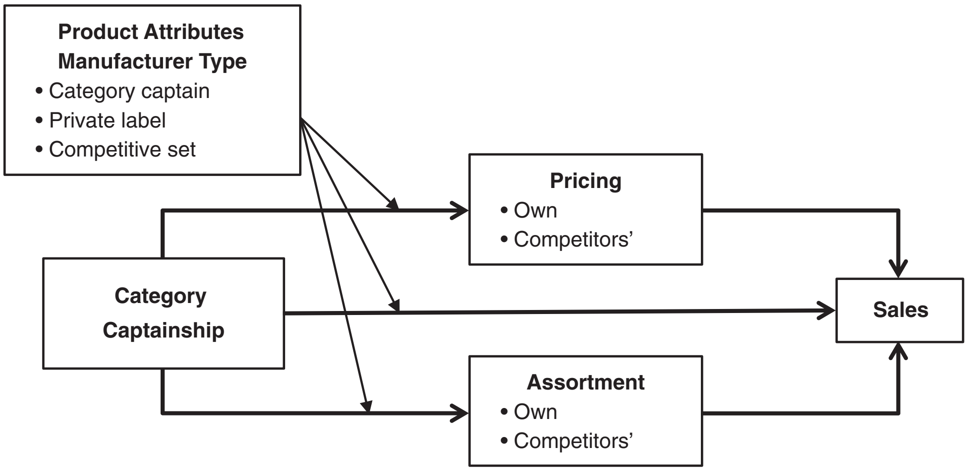
Two opposing forces affect retail prices for the competing manufacturer's products. On the one hand, the competing manufacturers may respond to the captain's and private label's price reductions by reducing their wholesale prices, which may allow the retailer to lower those products' retail prices. On the other hand, product attributes and cross-price effects may influence pricing decisions. In particular, the competing manufacturers' products that are in direct competition with the captain's products and/or private label products may be priced high to ensure that the captain's products and private label products are better positioned against their close competitors. Although we do not have data on wholesale prices, these two forces suggest that the retail prices for the competing manufacturers' may increase or decrease after the CC implementation.

Impact of CC on assortment. Our theoretical discussion suggests that the captain's products may receive a preferential treatment after CC. Furthermore, the captain's attempt to increase private label sales may create a similar preferential treatment for the private label. Drawing on these observations, we expect that the CC implementation will increase the assortment presence of the captain's products and private label products. Our theoretical discussion also suggests that the competing manufacturers' products may experience an increase or a decline in their assortment presence. From the findings related to the captain's opportunistic behavior, we anticipate that the competing manufacturers' products that are close substitutes to the captain's products may experience a decline in their assortment presence. In contrast, the competing manufacturers' products that are not in direct competition with the captain's products may experience an increase in their assortment presence so that category sales are increased. Because the retailer may protect its private label, a product's similarity to the private label may also negatively influence its assortment presence.

Impact of CC on sales. Our conceptual framework depicted in Figure 1 suggests that CC may influence a product's sales through three mechanisms: pricing, assortment, and merchandising. First, the impact of pricing on a product's sales

[1]For instance, 4 of the 11 performance criteria *Progressive Grocer* used to identify successful category captains in its 2016 category captains of the year article emphasize sales, whereas none of the criteria emphasize profitability (*Progressive Grocer* 2016, p. 42). Indeed, more than half of the 62 CC examples provided in the article report implementation results based on sales, whereas only 4 examples mention profitability.

FIGURE 1
Conceptual Framework and Directional Expectations for the Impact of the CC on Sales for a Particular Product



Directional Expectations			
	Manufacturer Type		
	Private Label	Category Captain	Other Manufacturers
Impact of CC on price	–	–	+/
Impact of CC on assortment	+	+	+/
Impact of CC on sales	+	+	+/

Notes: Pricing and assortment boxes illustrate that the CC implementation affects pricing and assortment, which in turn affect sales through own and cross-elasticities. Because our data set does not include any variables on merchandising, we model merchandising as a direct link from CC to sales. Manufacturer type and product attributes moderate the impact of CC on pricing, assortment, and merchandising changes. We discuss the empirical operationalization of these three mechanisms in the "Model" section.

will be determined by a combination of own- and cross-price effects. We expect the own-price elasticity to be negative and the cross-price elasticity to be positive. Second, the impact of assortment changes on a product's sales will be determined by own- and cross-assortment effects. We expect the own-assortment elasticity to be positive and the cross-assortment elasticity to be negative. Third, the impact of CC might go beyond pricing and assortment changes because the captain may also make merchandising recommendations. In line with our theoretical discussion, we expect that the captain's recommendations on pricing, assortment, and merchandising (if provided) will each have a positive impact on the sales of a private label product or a product that belongs to the captain. However, the impact of those recommendations on a competing manufacturer's product might be positive or negative, depending on whether that product is in close competition with the captain's products or private label products, as determined by the products' similarity.

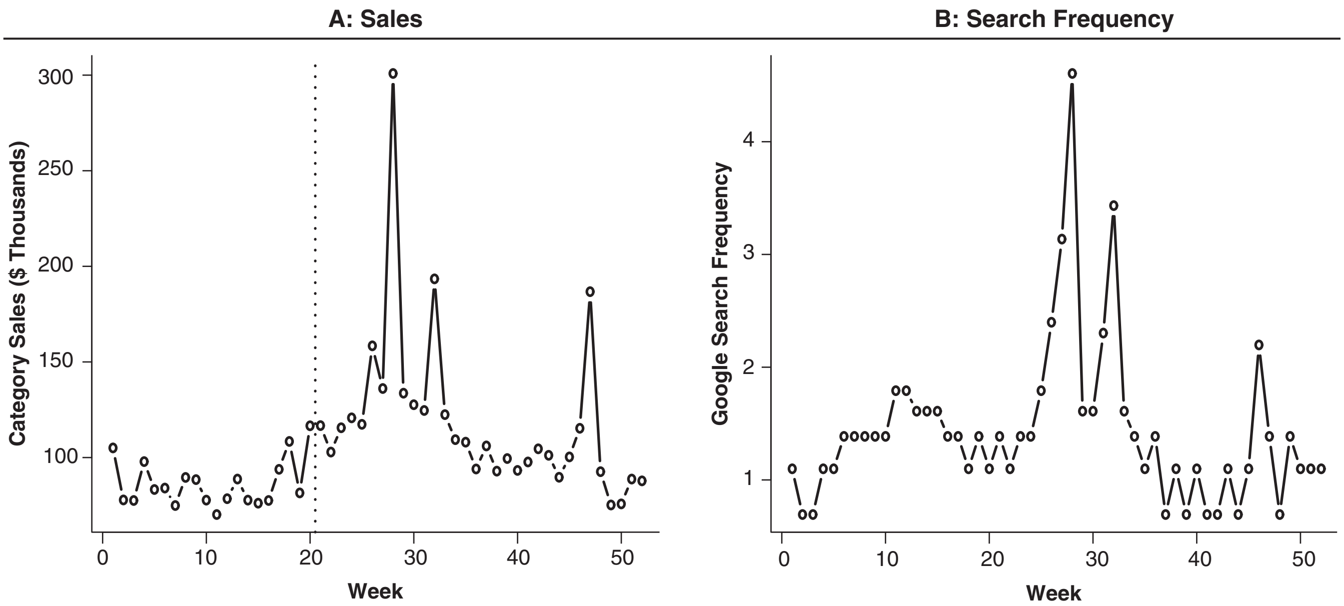
Research Setting

Implementation Summary

The retailer we study is a grocery chain that serves multiple states within one of the major geographical regions in the United States. It is one of the largest grocery retailers in its region in terms of market share and sales volume. The retailer has a reputation for offering high-quality products. The category we study is a mature, shelf-stable food category (i.e., a center-store grocery product). As per the retailer's request, the soon-to-be captain manufacturer provided the retailer with a strengths, weaknesses, opportunities, and threats (SWOT) analysis of the category.

The main findings of the captain's SWOT analysis, which we obtained from a presentation given by the captain to the retailer prior to the CC implementation, were as follows. The main strengths were the retailer's strong reputation as the provider of high-quality grocery products, its local market familiarity, and its loyal customer base. The main weakness was the retailer's lack of category knowledge, leading to poor assortment and pricing decisions. In particular, the captain had identified that despite offering a similar assortment with respect to its competitors, the retailer's average unit price of \$.72 in this category was \$.07 higher than the rest of market. Moreover, the average unit price for the retailer's private label was \$.66, which was \$.13 higher than its competitors' private labels. The biggest opportunities were to leverage the retailer's reputation and the captain's category knowledge to improve private label performance and increase category revenues. The main threat for the retailer was to lose further market share to its competitors. In light of the captain's SWOT analysis, the retailer decided to receive additional help through a formal CC implementation. Under the captain's guidance, assortment and pricing recommendations were generated and implemented.

FIGURE 2
The Weekly Category Sales and Search Frequency for the Category in the Same Period



Data Description

Our data set spans 52 weeks and consists of weekly Universal Product Code (UPC)–level measures for all products in the category. In week 21, the retailer modified the category using the services of a captain, which is the second-largest manufacturer in the category after the private label. Our data are aggregated to the firm level and include the following metrics for product i in week t:

- Sales revenue, r_{it}: The cumulative sales revenue generated from all stores.
- Sales quantity, q_{it}: The cumulative number of units (packages) sold across all stores.
- Product distribution, d_{it}: The percentage of stores that carry a particular product, weighted by the relative size of those stores. Formally, this measure of distribution is referred to as the all commodity volume–weighted distribution, which refers to the total annual sales revenue of a given store.
- Product size, z_i: Volume of product i in ounces.

The aggregated structure of our data set prevents us from observing store- and product-level promotions and discounts. However, having access to r_{it}, q_{it}, d_{it}, and z_i enables us to compute the average per ounce price consumers paid for product i in week t. Specifically, when product i is carried in the assortment in week t (i.e., when $d_{it} > 0$), we define its average volumetric price (i.e., price per ounce) as

$$p_{it} = \frac{r_{it}}{q_{it} z_i}. \tag{1}$$

Moreover, our data set includes a base price for each product. When a product is not carried in the assortment in a particular week (i.e., when $d_{it} = 0$, $q_{it} = 0$, and $r_{it} = 0$), we use this base price (after converting it to a volumetric price) as p_{it}.

Figure 2, Panel A, shows that weekly sales are higher during the postimplementation period. It also shows that there are three spikes in the weekly category sales in weeks 28, 32, and 47, which correspond to Thanksgiving, Christmas, and Easter, respectively. Thus, at least some of the increase in sales might be driven by seasonality and increased consumption in these three weeks. Presumably, when the consumption of a food item increases, consumers are more likely to search the web for recipes with the item of interest as an ingredient. Thus, we would expect the search frequency to capture a portion of variation in weekly sales. Figure 2, Panel B, shows the relative search frequency of the search phrase “category name recipe” in log scale. We obtain search frequency data from Google Trends, which is a publicly available web page providing time series data regarding the relative search frequency of a keyword or search phrase. We observe a strong positive correlation of .83 between weekly sales and web search patterns. Accordingly, we use g_t, which denotes the web search frequency for the category in week t, to control for seasonality. We also control for holiday effects by including a dummy variable, h_t, that assumes a value of 1 if a national holiday occurs in week t.

There are ten manufacturers in our data set. Each manufacturer owns one brand in the category. Accordingly, we use manufacturer and brand interchangeably herein. Table 1 provides an overview of these manufacturers offering a total of 110 UPCs. The private label has the largest share both in terms of the number of UPCs and sales revenue. It offers low-price products with an average volumetric price of $.07 during the preimplementation period. The category captain is the second largest manufacturer. It offers premium products with an average volumetric price of $.11 during the preimplementation period. The remaining eight manufacturers offer a total of 44

TABLE 1
An Overview of Each Manufacturer's Weekly Sales Before and After CC Implementation

Firm	# of UPCs	Weekly Sales Pre-CC ($)			Weekly Sales Post-CC ($)			% Change in Avg. Sales
		Mean	Median	SD	Mean	Median	SD	
1 (PL)	38	40,625	37,134	11,127	50,894	45,920	12,360	25.28%
2 (CC)	28	18,587	18,072	2,092	40,076	24,529	39,896	115.61%
3	16	10,739	10,684	1,354	6,947	6,419	2,329	–35.31%
4	13	8,668	7,341	5,218	12,317	8,347	9,492	42.10%
5	3	4,975	4,632	677	5,333	5,132	918	7.21%
6	4	2,112	2,088	414	1,684	1,419	735	–20.28%
7	4	296	298	31	286	263	77	–3.61%
8	1	229	230	40	252	243	43	10.03%
9	1	54	53	11	81	73	47	50.52%
10	2	0	0	0	552	538	290	—
All firms	110	86,285	82,385	12,438	118,421	107,082	42,864	37.24%

Notes: PL = private label.

UPCs. Some competing manufacturers offer low-price products, whereas others offer premium products. For instance, the average volumetric prices for manufacturers 3 and 4 during the preimplementation period are \$.08 and \$.13, respectively.

The weekly average category sales are 37.24% higher after CC. The increase in sales after the implementation is disproportionately higher for the captain's products compared with the competing manufacturers' products. For example, Table 1 shows that the total average weekly sales of the captain increased from \$18,587 to \$40,076, whereas the third manufacturer's total average weekly sales decreased from \$10,739 to \$6,947.

The key decision unit in a category management initiative is the subcategory or switching level, rather than the category itself. In this context, a subcategory is defined as a collection of products presumed to have similar product characteristics. For example, in the sugar and sweeteners category, subcategories would include brown sugar, granulated sugar, powdered sugar, artificial sweeteners, and so on. Our data set consists of nine subcategories. Larger subcategories typically have more manufacturers. The private label and the captain have a presence in all subcategories.

Because a subcategory is more homogeneous than a category in terms of product characteristics, it is usually assumed that the collection of products in a subcategory are perfect or near-perfect substitutes (Kök and Fisher 2007). Figure 3 illustrates that such a substitution pattern is unlikely to hold in our data set. For instance, Figure 3, Panel A, shows that most products in subcategory 2 have a volume of ~15 oz., but ~8 oz. and ~11 oz. products are also available in the assortment. Similarly, Figure 3, Panel B, illustrates that some ~15 oz. products in subcategory 4 are relatively cheap, with volumetric prices around \$.09 per ounce, whereas another ~15 oz. product in the same subcategory has a volumetric price of \$.14 per ounce. These examples indicate that substitution among similar products (in terms of volumetric price and size) can be higher than substitution among dissimilar ones. Such a substitution pattern is likely to affect assortment changes made during the CC initiative. Accordingly, we control for product similarity in our empirical analysis. We measure the similarity between products i and j in the same subcategory s using the following metric:

$$\text{(2)} \qquad \delta_{ij} = 1 - \sqrt{.5\left(\frac{\bar{p}_i - \bar{p}_j}{\bar{p}^s_{max} - \bar{p}^s_{min}}\right)^2 + .5\left(\frac{z_i - z_j}{z^s_{max} - z^s_{min}}\right)^2}.$$

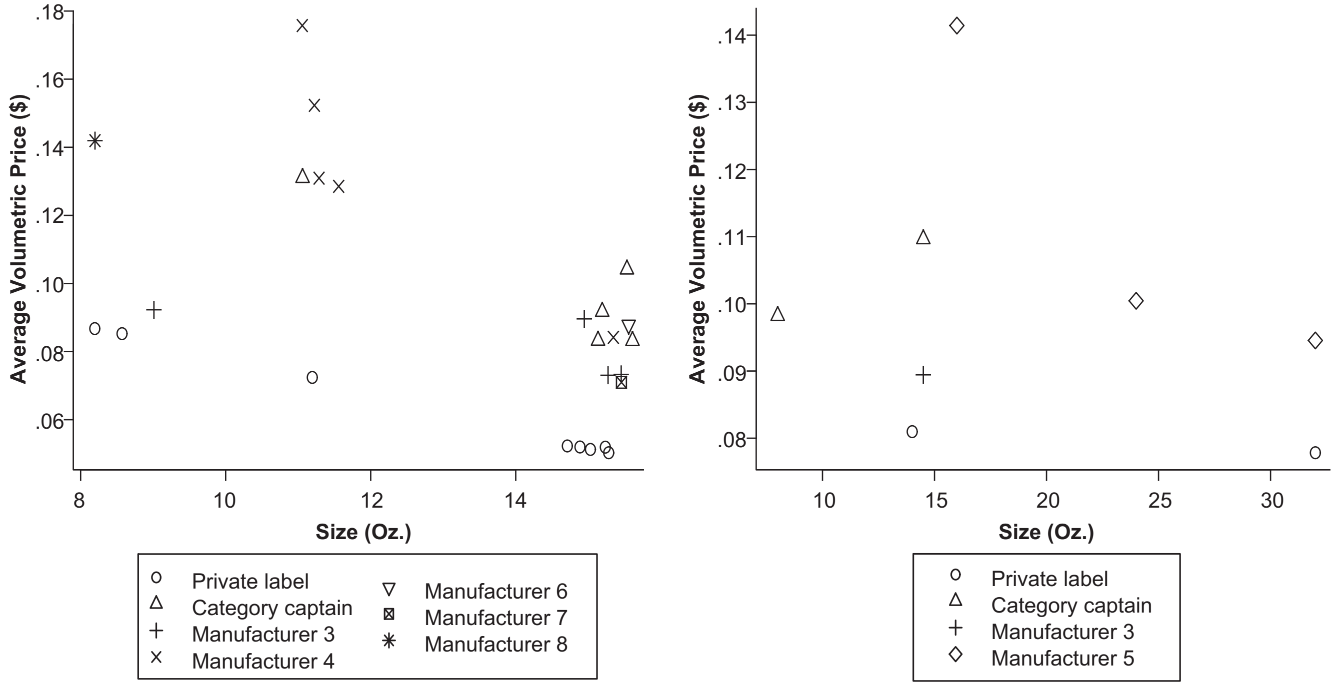
In Equation 2, z_i is the package size, and $\bar{p}_i \equiv (1/20)\sum_{t=1}^{20} p_{it}$ is the average volumetric price prior to the CC implementation for product i. In addition, $\bar{p}^s_{max}$ and $\bar{p}^s_{min}$ are the average volumetric prices of the most expensive and the cheapest products in subcategory s, respectively. Similarly, z^s_{max} and z^s_{min} are the sizes of the largest and the smallest products by volume in subcategory s, respectively. $\bar{p}^s_{max} - \bar{p}^s_{min}$ and $z^s_{max} - z^s_{min}$ allow us to normalize the impact of volumetric price and size, respectively, so that δ_{ij} takes values in the unit interval $[0, 1]$. As such, two products with the exact same size and average volumetric price would have a similarity score of 1.[2]

Figure 4, Panel A, demonstrates the change in the average distribution of every UPC in our data set after CC. We observe that a vast majority of products offered by the private label (manufacturer 1), the category captain (manufacturer 2), and manufacturer 4 experience an increase in their distributions. Conversely, most of manufacturer 3's products experience a decline in their distributions. Recall from Table 1 that the average weekly sales of manufacturers 1, 2, and 4 increase, whereas manufacturer 3 experiences a decline in sales after CC. These observations are consistent with our conceptual framework suggesting that the assortment changes made during the

[2]An alternative way to define product similarity is to incorporate subcategory and brand into δ_{ij}. For instance, δ_{ij} can be defined as $\delta_{ij} = 1 - \sqrt{.25[(\bar{p}_i - \bar{p}_j)/(\bar{p}^s_{max} - \bar{p}^s_{min})]^2 + .25[(z_i - z_j)/(z^s_{max} - z^s_{min})]^2 + .25\mathbb{I}^M_{ij} + .25\mathbb{I}^S_{ij}}$, where $\mathbb{I}^M_{ij}$ is an indicator variable that takes a value of 0 if i and j belong to the same manufacturer, and 1 otherwise, and $\mathbb{I}^S_{ij}$ is an indicator variable that takes a value of 0 if i and j are in the same subcategory, and 1 otherwise. Incorporating brand and subcategory effects into our similarity metric does not change our findings. Thus, we use Equation 2 in our analysis because of its parsimony. The Web Appendix provides estimation results for alternative model specifications that incorporate subcategory and brand into our similarity metric.

FIGURE 3
Product Positions with Respect to the Average Volumetric Price and Product Size in Subcategories 2 and 4

A: Subcategory 2 | **B: Subcategory 4**



implementation will benefit the private label and the captain's products and that such changes may explain changes in sales.

Figure 4, Panel B, shows the change in the average volumetric price of every UPC in our data set. The average volumetric price declines for most products after CC. This observation is aligned with the theoretical predictions in the literature regarding the impact of CC on prices (Kurtuluş and Toktay 2011; Nijs, Misra, and Hansen 2014). Consistent with our conceptual framework, declining prices could be another reason for the increase in sales after CC.

Model

We study the impact of CC on sales by building an empirical model based on our conceptional framework illustrated in Figure 1. Specifically, we estimate a simultaneous system of equations in which we allow CC to exert both a direct and indirect (through price and assortment) influence on sales. We specify each equation in log-log form, which enables us to interpret a model coefficient as the expected proportional change in the dependent variable per proportional change in the independent variable (Gelman and Hill 2006). Furthermore, log-log model specification leads to mathematically tractable expressions regarding the impact of the CC implementation on prices, assortment, and sales. Logarithmic demand models have been used extensively in both marketing and economic applications (Hanssens, Parsons, and Schultz 2003; Lilien, Kotler, and Moorthy 1992). Because our data follow a panel structure, we fit a hierarchical model that allows for heterogeneity in parameters for each individual UPC. We begin by specifying the direct impact of CC and other demand-generating factors on volumetric sales using the following specification:

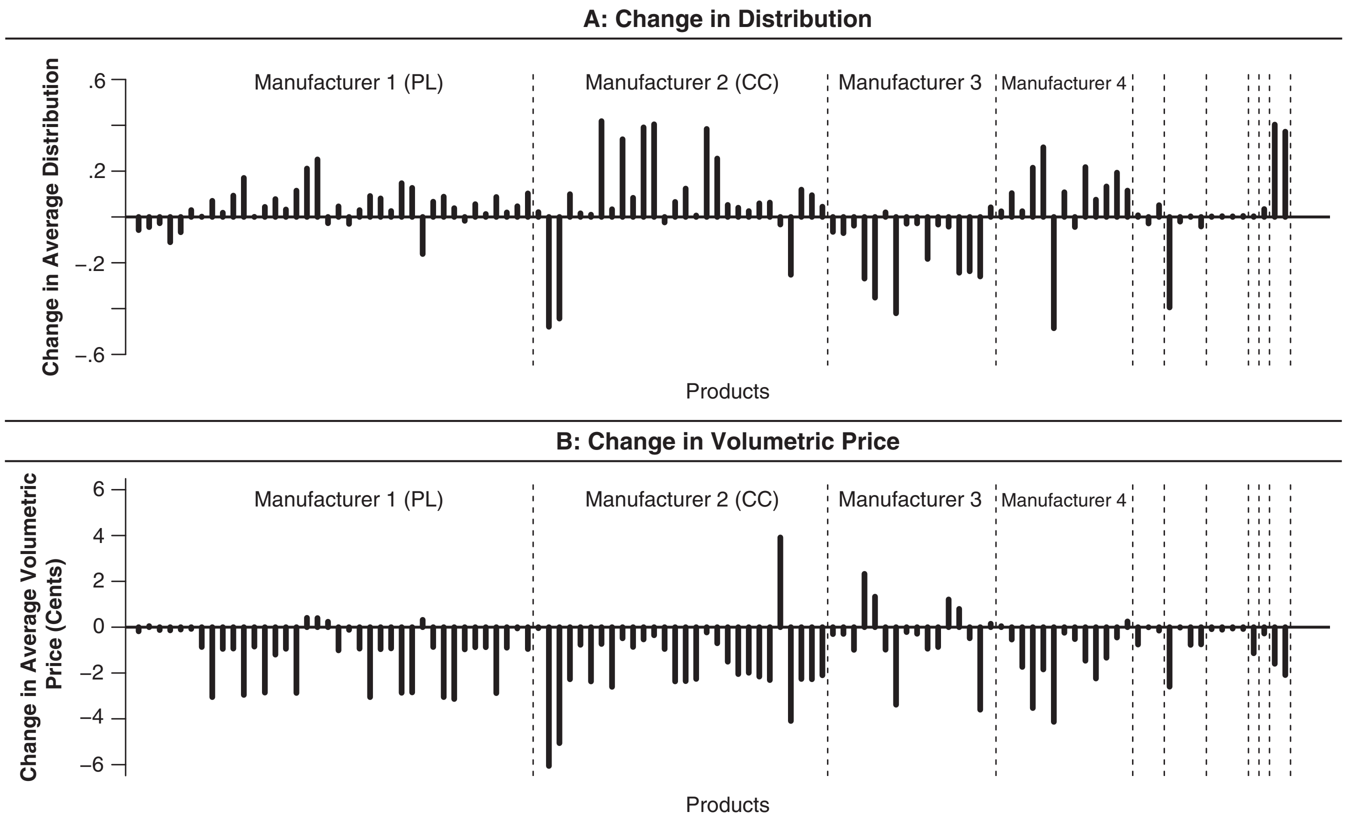
$$\log(v_{it}) = \beta_{0i} + \beta_{1i}\log(p_{it}) + \beta_{2i}\overline{p}_{it} + \beta_{3i}\log(d_{it}) + \beta_{4i}\overline{d}_{it} + \beta_{5i}\log(g_t) + \beta_{6i}h_t + \beta_{7i}t + \beta_{8i}\mathbb{I}(t > \tau) + \varepsilon^{s}_{it}, \quad (3)$$

where

- v_{it} are volumetric sales (i.e., $q_{it} \times z_i$) for UPC i in week t,
- $\overline{p}_{it}$ is an index of competitive prices for UPC i in week t. We construct this index by computing a weighted average logarithmic volumetric price of all other products in UPC i's subcategory. Formally, $\overline{p}_{it} = \sum_{j\in\mathscr{A}_{s(i)}\setminus\{i\}} w_{ij}\log(p_{jt})$, where $\mathscr{A}_{s(i)}$ denotes the set of products that belong to product i's subcategory, s(i), and $w_{ij} = \delta_{ij}/(\sum_{k\in\mathscr{A}_{s(i)}\setminus\{i\}}\delta_{ik})$ is the weight of product j, which captures the notion that products with similar attributes (i.e., high w_{ij} values) are closer competitors.
- $\overline{d}_{it}$ is an index of competitive distribution for UPC i in week t. We measure the competitive distribution index as a weighted average logarithmic distribution of all other products in UPC i's subcategory. Formally, $\overline{d}_{it} = \sum_{j\in\mathscr{A}_{s(i)}\setminus\{i\}} w_{ij}\log(d_{jt})$.[3]

[3]We calculate cross-price and cross-distribution at the subcategory level because a subcategory is more homogeneous than a category in terms of product characteristics. Alternatively, one can calculate cross-price and cross-distribution using weights (i.e., w_{ij} values) derived from similarity scores calculated at the category level (e.g., the formula presented in footnote 2). Calculating cross-price and cross-distribution at the category level does not change our findings. The Web Appendix provides estimation results for an alternative model specification with category-level cross-price and cross-distribution variables.

FIGURE 4
Change in Average Weekly Distribution and Volumetric Price for Each Product



Notes: PL = private label. Each bar represents a UPC. The vertical dashed lines separate different manufacturers. The manufacturers are displayed in a decreasing order from left to right in line with the preimplementation average weekly sales revenues. The change in the average weekly distribution for UPC i is computed as $\Delta d_{it} = (1/32)\sum_{t=21}^{52} d_{it} - (1/20)\sum_{t=1}^{20} d_{it}$. The change in the average weekly volumetric price is computed similarly.

- t is a linear indicator of time that enables us to model trend in the time series.
- $\mathbb{I}(t > \tau)$ is an indicator variable that is equal to 0 in the weeks preceding CC and is equal to 1 in the weeks following. The variable τ denotes the week of implementation.

Finally, as defined in the previous section, g_t and h_t denote the search frequency and holiday dummies, respectively. Equation 3 allows us to understand the direct impact of CC on sales performance through β_{8i}. Because we define merchandising as all demand-enhancing actions excluding pricing and assortment, we interpret β_{8i} as the impact of merchandising on product i's volumetric sales.[4] We capture the indirect impact of CC on sales through pricing and assortment by building a system of equations as follows:

$$(4)\quad \log(p_{it}) = \alpha_{0i} + \alpha_{1i}\log(g_t) + \alpha_{2i}h_t + \alpha_{3i}\mathbb{I}(t > \tau) + \varepsilon_{it}^{p}, \text{ and}$$

$$(5)\quad \log(d_{it}) = \gamma_{0i} + \gamma_{1i}\log(g_t) + \gamma_{2i}h_t + \gamma_{3i}\mathbb{I}(t > \tau) + \varepsilon_{it}^{d}.$$

[4]While our data set does not have any variables that enable us to quantify the impact of specific merchandising efforts, it is plausible that the CC implementation may have led to some merchandising changes (e.g., new shelf displays, reallocation of shelf space among products; Subramanian et al. 2010). β_{8i} captures the aggregate impact of such merchandising efforts.

In Equations 4 and 5, coefficients $\{\alpha_{1i}, \alpha_{2i}\}$ and $\{\gamma_{1i}, \gamma_{2i}\}$ control for seasonality and holiday effects, whereas coefficients α_{3i} and γ_{3i} capture the impact of CC on UPC i's price and distribution, respectively.

We allow for correlation in the cross-equation error terms by assuming a multivariate normal structure for the joint distribution of $\{\varepsilon_i^s, \varepsilon_i^p, \varepsilon_i^d\} \sim N(0, \Sigma_i)$. By doing so, we control for the potential of unobserved demand shocks that could affect our ability to infer the true impact of CC on sales performance. Σ_i is a 3×3 covariance matrix that captures the degree to which unobserved shocks to our demand system jointly influence price, distribution, and sales.

Because our model is estimated using hierarchical Bayesian methods, we complete the hierarchy by specifying a distribution of heterogeneity over the complete vector of regression coefficients (Rossi, Allenby, and McCulloch 2005):

$$(6)\qquad \{\beta_i, \alpha_i, \gamma_i\} \sim N(\Delta w_i, \Omega),$$

where w_i are UPC-specific characteristics that can moderate the relationship between CC and sales, price, and distribution. Δ is an estimated matrix of coefficients that characterize this relationship, and Ω is a full covariance matrix that captures cross-UPC correlation in the estimated coefficients. Included in w_i are the following variables:

- $\mathbb{I}(i \in CC)$ is an indicator variable that is equal to 1 if UPC i belongs to the category captain. The reference level for this variable is the private label, so the resulting coefficient should be interpreted as one deviation away from the average private label effect.
- $\mathbb{I}(i \in CS)$ is an indicator variable that is equal to 1 if UPC i belongs to a manufacturer that is in the competitive set, CS. The competitive set includes all manufacturers in the category, except the private label manufacturer and the captain. This variable's effect should also be interpreted with respect to the private label.
- Sim_i^{PL} is a continuous variable that measures the similarity between UPC i and the private label products in UPC *i*'s subcategory. Let $\mathscr{A}_s^{PL}$, $\mathscr{A}_s^{CC}$, and $\mathscr{A}_s^{CS}$ denote the subset of products offered by the private label, captain, and competing manufacturers in subcategory s, respectively. For UPC i, we calculate Sim_i^{PL} as

$$Sim_i^{PL} = \max_{j \in \mathscr{A}_s^{PL}} \delta_{ij}. \tag{7}$$

In words, Sim_i^{PL} is the maximum similarity between UPC i and the private label products in its subcategory. A high Sim_i^{PL} value indicates that UPC i has a close substitute offered by the private label manufacturer. By definition, $Sim_i^{PL} = 1$ for private label products. As we discussed in the "Theoretical Background" section, similar attribute-based substitution models are used in the choice modeling and assortment literature streams (e.g., Hoch, Bradlow, and Wansink 1999; Rooderkerk, Van Heerde, and Bijmolt 2011, 2013).

- Sim_i^{CC} is a continuous variable that measures the similarity between UPC i and the category captain's products in UPC i's subcategory. We compute this variable as $Sim_i^{CC} = \max_{j \in \mathscr{A}_s^{CC}} \delta_{ij}$. By definition, $Sim_i^{CC} = 1$ for the captain's products.[5]

We include $\mathbb{I}(i \in CC)$, $\mathbb{I}(i \in CS)$, Sim_i^{PL}, and Sim_i^{CC} in our upper-level model as covariates because the impact of the CC implementation may differ by manufacturer type as well as whether a product is in direct competition with a product offered by the private label manufacturer or the captain. We estimate the parameters of the hierarchical model specified by Equations 3, 4, 5, and 6 using standard Bayesian methods (Rossi, Allenby, and McCulloch 2005). Specifically, we use a hybrid sampler where the collection of regression parameters for each UPC, $\{\beta_i, \alpha_i, \gamma_i\}$, are drawn using the Metropolis–Hastings algorithm. Conditional on a realization of the regression parameters for all UPCs, we use a Gibbs draw for both Σ_i and the parameters in the upper level, Δ and Ω. We ran the sampler for 100,000 iterations and used the final 50,000 draws for inference.

[5]An alternative way to measure a product's similarity to private label or CC is to calculate an average similarity score (e.g., $(1/|\mathcal{A}_s^{CC}|)\sum_{j \in \mathscr{A}_s^{CC}} \delta_{ij}$). Our findings remain qualitatively unchanged when we use the average similarity (instead of the maximum similarity) scores as explanatory variables. We opt in for maximum similarity scores because they better capture close competition between two UPCs with similar attributes, whereas the average similarity scores are less informative about close competition between similar products.

After estimating model parameters, we quantify the effect of the CC implementation by measuring its impact on category sales revenues. Using volumetric sales and volumetric prices, the sales revenue for UPC i in week t can be expressed as $r_{it} = v_{it}p_{it}$. In the log form, we have $\log(r_{it}) = \log(v_{it}) + \log(p_{it})$. Using the expression for $\log(v_{it})$ specified in Equation 3, we obtain

$$\begin{aligned} \log(r_{it}) = {} & \beta_{0i} + (1+\beta_{1i})\log(p_{it}) + \beta_{2i}\bar{p}_{it} + \beta_{3i}\log(d_{it}) + \beta_{4i}\bar{d}_{it} \\ & + \beta_{5i}\log(g_t) + \beta_{6i}h_t + \beta_{7i}t + \beta_{8i}\mathbb{I}(t > \tau) + \varepsilon_{it}^s. \end{aligned} \tag{8}$$

Accordingly, we measure the impact of the CC implementation on UPC i's sales revenues by taking a partial derivative of Equation 8 with respect to $\mathbb{I}$, the CC indicator variable. That is,

$$\begin{aligned} \frac{\partial \log(r_{it})}{\partial \mathbb{I}} = {} & (1+\beta_{1i})\frac{\partial \log(p_{it})}{\partial \mathbb{I}} + \beta_{2i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\frac{\partial \log(p_{jt})}{\partial \mathbb{I}} \\ & + \beta_{3i}\frac{\partial \log(d_{it})}{\partial \mathbb{I}} + \beta_{4i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\frac{\partial \log(d_{jt})}{\partial \mathbb{I}} + \beta_{8i}. \end{aligned} \tag{9}$$

Because CC influences prices and distribution, the right-hand side of this equation has partial derivatives of the price, cross-price, distribution, and cross-distribution variables with respect to $\mathbb{I}$. Differentiating the price and the distribution equations of our empirical model, 4 and 5, with respect to $\mathbb{I}$ gives $\partial\log(p_{it})/\partial\mathbb{I} = \alpha_{3i}$ and $\partial\log(d_{it})/\partial\mathbb{I} = \gamma_{3i}$, respectively. Therefore, we can rewrite Equation 9 as

$$\begin{aligned} \frac{\partial \log(r_{it})}{\partial \mathbb{I}} = {} & (1+\beta_{1i})\alpha_{3i} + \beta_{2i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\alpha_{3j} + \beta_{3i}\gamma_{3i} \\ & + \beta_{4i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\gamma_{3j} + \beta_{8i}. \end{aligned} \tag{10}$$

In Equation 10, $(1+\beta_{1i})\alpha_{3i} + \beta_{2i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\alpha_{3j}$ captures the total impact of the changes in UPC i's price and the competitors' prices, $\beta_{3i}\gamma_{3i} + \beta_{4i}\sum_{j \in \mathscr{A}_{s(i)} \backslash \{i\}} w_{ij}\gamma_{3j}$ captures the impact of the changes in UPC i's and its competitors' distribution, and β_{8i} captures the impact of merchandising efforts on UPC i's sales. In the next section, we use Equation 10 to measure and decompose the impact of CC on the entire category as well as the individual manufacturers.

Results

Table 2 shows the coefficient estimates for the sales, price, and distribution equations specified in Equations 3, 4, and 5, respectively. We report the posterior mean and 95% interval for each coefficient. The CC indicator coefficient in the sales equation indicates that merchandising efforts increase category sales by 8.6%, which is significant at $p < .05$. (Hereinafter, we report statistical significance at $p < .05$.) We also find that the search frequency variable is positively correlated with sales. The holiday indicator variable is insignificant, which implies that the search frequency variable captures not only seasonality but also the sales spikes observed during holidays. Consistent with the well-known impact of pricing, a product's sales decrease in its own price and increase in its competitors' prices.

TABLE 2
Coefficient Estimates of the Sales, Price, and Distribution Equations

	Sales Equation			Price Equation			Distribution Equation		
	Mean	LB	UB	Mean	LB	UB	Mean	LB	UB
Intercept	**6.603**	6.510	6.700	**–2.405**	–2.504	–2.304	**.610**	.512	.702
Own price	**–1.393**	–1.500	–1.300						
Cross-price	**.145**	.053	.230						
Own distribution	**1.548**	1.461	1.642						
Cross-distribution	.024	–.065	.111						
Search frequency	**.193**	.105	.277	**–.138**	–.216	–.061	.021	–.092	.093
Holiday	.088	–.008	.177	**–.122**	–.199	–.040	.017	–.061	.099
Linear trend	–.005	–.081	.072						
CC indicator	**.086**	.001	.166	**–.092**	–.169	–.004	.020	–.062	.099
# of UPCs		110			110			110	
Sample size		5,720			5,720			5,720	
R^2		.905			.317			.357	

Notes: We report coefficient estimates for Equations 3, 4, and 5. LB and UB are the 2.5% and 97.5% quantiles of the estimated parameter's posterior distribution, respectively. Statistically significant values at the 95% level are highlighted in bold.

Sales increase in own-distribution, but we do not find a direct relationship between competitive distribution and sales.[6] Finally, there is no time trend in sales.

The CC indicator coefficient in the price equation indicates that CC leads to a 9.2% decline in volumetric prices, which is statistically significant. Both the holiday indicator and search frequency variables are negative and significant, indicating that the sales increases during the holiday weeks are in part due to the steep price reductions in those weeks. The CC indicator coefficient in the distribution equation is insignificant. That is, we do not observe a systematic increase or decline in the overall distribution offered by the retailer in this category, on average.

After estimating the model coefficients, we use Equation 10 to quantify the impact of CC on different stakeholders. Specifically, we first use the posterior distributions of the coefficients that appear in Equation 10 to obtain the impact of merchandising, assortment, and pricing changes on UPC i's sales revenues. Then, we calculate the impact of CC on a product subset (e.g., the captain's products) by taking a weighted average of the impacts on each UPC in that subset, where the weight for each UPC equals its pre-implementation market share within that subset. Table 3 shows the impact of CC on the entire category as well as the manufacturers.

[6]Our UPC-level analysis (not reported herein because of space limitations) revealed that the insignificance of the cross-distribution variable at the aggregate level is driven by two factors. First, a small number of high-demand UPCs are insensitive to the presence of substitute products. Second, own- and cross-distribution variables move in the opposite directions for some UPCs. For instance, if a product's distribution score declines, its close competitors' distribution scores increase, creating a colinear relationship between own- and cross-distribution variables. For these two reasons, the cross-distribution variable is insignificant at the aggregate level. Nevertheless, we show that demand substitution plays a crucial role in shaping the postimplementation assortment.

Impact of the CC Implementation on Sales

Table 3 shows that the increase in category sales that can be associated with CC is 19.1%, which is statistically significant. The pricing changes boost category sales by 7.6%. The assortment changes increase sales by 2.9%. Finally, merchandising efforts lead to a 8.6% increase in category sales. The impacts of pricing, assortment, and merchandising on category sales are all statistically significant. Table 3 also shows that CC leads to a 13.9% increase in private label sales and a 42.4% increase in the captain's sales. The impacts of merchandising, pricing, and assortment are all significant for both the private label and the captain's products.

Our analysis shows that some manufacturers benefit from CC, whereas others suffer as manifested by declining sales. For instance, Table 3 shows that CC decreases manufacturer 3′s sales by 18.2%. This decrease is driven by the decline in the presence of manufacturer 3's products in the assortment. Manufacturer 6 experiences a sales decline as well. The decrease in manufacturer 6's sales due to CC is 33.4%. A large portion of this decrease (i.e., 15.6%) is driven by the decline of manufacturer 6's presence in the assortment. Contrary to manufacturers 3 and 6, manufacturer 4 benefits because CC increases its sales by 37.1%. Most of this increase (i.e., 19.3%) is due to assortment changes. The impact of CC on manufacturer 5's sales is statistically insignificant. The remaining four manufacturers have relatively small sales, which makes it difficult to provide reliable estimates at a manufacturer level. However, the total impact of CC on these four manufacturers is positive, as manifested by a 13.1% increase in their total sales that can be attributed to CC.

There are two main observations that emerge from analyzing the changes in sales by manufacturer. First, both the private label and the category captain's products benefit from CC. Second, some competing manufacturers also benefit from CC, whereas others suffer as manifested by their declining presence in the assortment and lower sales. While the first observation is aligned with the theoretical predictions in the literature, the second observation raises a follow-up question:

TABLE 3
The Decomposition of the Impact of Category Captainship by Manufacturer

	Impact of Merchandising			Impact of Price			Impact of Assortment			Total Impact		
Manufacturer	**Mean**	**LB**	**UB**	**Mean**	**LB**	**UB**	**Mean**	**LB**	**UB**	**Mean**	**LB**	**UB**
1 (PL)	**.045**	.035	.052	**.026**	.022	.030	**.068**	.052	.090	**.139**	.127	.155
2 (CC)	**.214**	.197	.232	**.092**	.085	.097	**.118**	.092	.142	**.424**	.396	.452
3	−.004	−.026	.029	−.013	−.029	.003	**−.165**	−.187	−.136	**−.182**	−.206	−.155
4	**.113**	.089	.143	**.065**	.046	.080	**.193**	.124	.235	**.371**	.311	.415
5	−.014	−.055	.059	**.037**	.025	.053	.023	−.022	.085	.045	−.013	.171
6	**−.187**	−.220	−.155	.008	−.020	.029	**−.156**	−.224	−.080	**−.334**	−.413	−.258
All other	**.109**	.087	.145	.009	−.003	.029	.013	−.026	.065	**.131**	.101	.185
Entire category	**.086**	.001	.166	**.076**	.066	.088	**.029**	.003	.043	**.191**	.177	.219

Notes. PL = private label. LB and UB are the 2.5% and 97.5% quantiles of the estimated impact, respectively. Statistically significant values at the 95% level are highlighted in bold.

Why do some competing manufacturers benefit from CC, whereas others experience adverse consequences? We address this question next.

Competitive Implications of Category Captainship

In this subsection, we focus on the products offered by the competing manufacturers and establish a link between product attributes and assortment changes. We begin our analysis with a motivating example. Table 4 provides a summary of product attributes in subcategory 9, which is the smallest subcategory in our data set. Comparing the pre- and postimplementation average distributions shows that product 2 offered by manufacturer 3 is removed from the category after CC.[7] A closer examination of product attributes reveals that product 1, which is a private label product, and product 2 have the same size and average volumetric price. Thus, one potential explanation for the removal of product 2 from the assortment is an attempt to increase private label sales by excluding the private label's close competitors.

In light of the aforementioned example from subcategory 9, we conjecture that a competing manufacturers' product is more likely to experience a decline in its distribution if there is a close substitute to that product offered by the private label manufacturer. Similarly, a product's similarity with the category captain's products may also have a negative impact on its assortment presence after CC. The hierarchical structure of our empirical model enables us to test our conjectures regarding the potential negative impact of a product's similarity to the private label and/or the captain's products. Table 5 reports the upper-level model coefficients for the CC indicator variables in the sales, price, and distribution equations (i.e., Equations 3–5). Because manufacturers 3 and 6 suffer and manufacturer 4 benefits from the assortment changes, we focus on the CC indicator coefficient of the distribution equation, γ_{3i}. For a particular UPC i offered by a competing manufacturer, our hierarchical model specification implies that the estimated value of γ_{3i} can be written as

$$(11)\quad \frac{\partial \log(d_{it})}{\partial \mathbb{I}} = \hat{\gamma}_{3i} = .020 + .002\mathbb{I}(i\in CC) - .087\mathbb{I}(i\in CS) - .249\mathrm{Sim}_i^{PL} + .255\mathrm{Sim}_i^{CC}, \text{ and}$$

$$(12)\quad = -.067 - .249\mathrm{Sim}_i^{PL} + .255\mathrm{Sim}_i^{CC},$$

where the second line follows because $\mathbb{I}(i\in CC) = 0$ and $\mathbb{I}(i\in CS) = 1$ for a product offered by a competing manufacturer. Equation 12 captures the estimated change in the assortment presence of a product offered by a competing manufacturer as a function of its similarity to the private label and the captain's products. The intercept, −.067, is statistically insignificant. The coefficient of Sim_i^{PL}, which measures the similarity between UPC i and the private label products in the same subcategory, is negative and significant. That is, a product is more likely to experience a decline in its assortment presence if there is a similar private label product in the assortment. Conversely, the coefficient of Sim_i^{CC}, which measures the similarity between UPC i and the captain's products in the same subcategory, is positive and significant. This finding implies that the competing manufacturers' products that are similar to the captain's products are more likely to increase their presence in the assortment during the postimplementation period.

These findings are consistent with the objectives of the CC implementation we study. In particular, decreasing the assortment presence of manufacturers 3 and 6, which are in direct competition with private label because of their low prices, leaves the private label as the most affordable option in each subcategory. Consequently, private label performance improves. Furthermore, increasing the assortment presence of manufacturer 4, which offers premium products, enables the retailer to enrich its assortment and thereby increase overall category sales. While the protection of private label is in line with the existing literature (e.g., Chintagunta 2002), the increased presence of manufacturer 4 contrasts the literature's predictions on the negative impact of CC on the competing manufacturers.

[7]The average distribution for product 2 during the postimplementation period is slightly above zero because it took the retailer a few weeks to completely remove this product from the assortment.

TABLE 4
Summary of Product Attributes in Subcategory 9

Product	Manufacturer	Size	Preimplementation Averages			Postimplementation Averages		
			Vol. Price	Dist.	Mkt. Share	Vol. Price	Dist.	Mkt. Share
1	Private label	14.5 oz.	$.06	.73	51%	$.05	.71	64%
2	Manufacturer 3	14.5 oz.	$.06	.28	20%	$.09	.02	1%
3	Category captain	14.5 oz.	$.12	.21	20%	$.11	.19	24%
4	Private label	8 oz.	$.11	.25	9%	$.08	.29	11%

Notes: We report the average values of volumetric price, distribution, and market share during the pre- and postimplementation periods.

What would have happened if the retailer had not protected its private label?[8] We address this question by revisiting Equation 11. This equation suggests that the retailer may be protecting its private label by reducing the assortment presence of the competing manufacturers' products that are in close competition with private label. Thus, we conjecture that such products would have had a greater assortment presence in the absence of private label protection. Increasing the assortment presence of those products would have influenced category sales through own- and cross-distribution effects.

We operationalize this conjecture by considering a scenario in which the coefficient for Sim_i^{PL} equals zero instead of its estimated value, −.249. Setting this coefficient to zero implies that a product's similarity to private label does not lead to a decline in its assortment presence after CC. For instance, revisiting the example presented in Table 4, product 2 in subcategory 9 has $\mathrm{Sim}_i^{PL} = 1$ because product 1, which is a private label product, has the same size and average volumetric price as product 2. Equation 11 suggests that this product's similarity to private label is associated with a $-.249 \times \mathrm{Sim}_i^{PL} = -.249$ decline in its assortment presence. Thus, in the absence of private label protection, we conjecture that this product's postimplementation distribution would have been higher by .249. This change would have also increased the cross-distribution values for the other products in the same subcategory. Applying the same logic to all products in the category enables us to calculate the expected own- and cross-distribution levels for each product in an alternative setting in which the private label is not protected. After calculating the new own- and cross-distribution levels for each product, we plug them into Equation 3 to calculate the impact of CC on each product's sales in this alternative setting.

Figure 5 reports how switching from the original CC implementation setting to an alternative setting in which the private label is not protected changes the impact of CC on the entire category as well as each manufacturer. In the alternative setting, the overall category sales would have been 4.1 percentage points higher than the increase we estimate under the original setting. That is, the impact of CC on category sales is 19.1% in the original setting as reported in Table 3, whereas it is 23.2% in the alternative setting. Private label sales decline by 3.2 percentage points when private label is not protected. However, its main competitor, manufacturer 3, experiences a 13.8-percentage-point increase in its sales. The sales changes for the remaining manufacturers in the category are mixed because changing Sim_i^{PL} affects not only a product's own distribution but also the distribution of the remaining products in the category. It is important to note that although total category sales are expected to increase under this alternative regime, this finding does not necessarily imply that the retailer made a mistake in protecting the private label. Because we do not observe product margins, it is possible that the increase in sales could be associated with a decrease in profitability.

[8]We thank the area editor for suggesting that we explore this question.

Robustness Tests

We examined alternative model specifications to assess the robustness of our findings. First, it is plausible that fitting a single coefficient for all competing manufacturers in the upper-level model may not fully capture the differences between manufacturers. Thus, we expanded the upper-level model variables (i.e., w_i) to include manufacturer-specific dummy variables. Expanding the set of upper-level model variables did not change our results. Second, we moved the product similarity variables Sim_i^{PL} and Sim_i^{CC} from the upper-level model to the lower model (i.e., Equations 3–5) to determine whether this change affects our findings. This alternative model specification also revealed that the competing manufacturers that offer close substitutes to the private label suffer from CC, whereas the competing manufacturers that closely compete with the captain benefit from CC. Our remaining findings (i.e., the impact of CC on various stakeholders) also remained unchanged. Finally, it is plausible that it took the retailer more than one week to fully implement CC. To ensure that implementation delays do not affect parameter estimates, we reran our analysis after dropping weeks 21–24, which gives the retailer four weeks for the CC implementation. Our results remained qualitatively similar in this alternative model specification, in which weeks 25–52 denote the postimplementation period.

Conclusion

Although CC has been implemented by many retailers and has been examined from a theoretical perspective, to the best of our knowledge, our study is a first attempt to empirically examine the outcomes of an actual CC implementation. Our research demonstrates how joint consideration of assortment and pricing, the presence of a private label, and product characteristics may influence the outcomes of CC implementations. Nevertheless, further research is needed to test whether our findings generalize

TABLE 5
Upper-Level Model Estimates for the CC Indicator Variables of the Sales, Price, and Distribution Equations

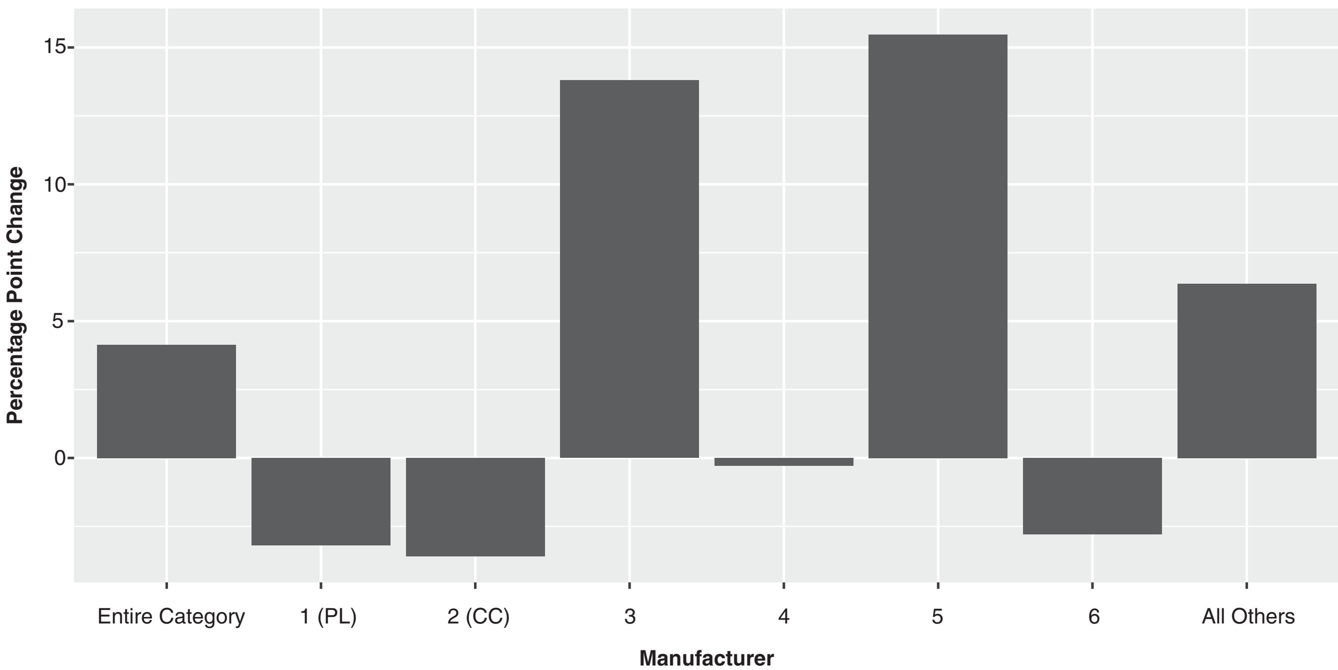
Equation	Variable	Mean	LB	UB
Sales, β_{8i}	Intercept	**.086**	.027	.140
	Category captain	**.181**	.022	.327
	Competitive set (excluding private label)	.000	–.231	.218
	Similarity to private label	.004	–.573	.506
	Similarity to category captain	.000	–.404	.395
Price, α_{3i}	Intercept	**–.138**	–.193	–.083
	Category captain	–.017	–.145	.117
	Competitive set (excluding private label)	.065	–.146	.290
	Similarity to private label	–.001	–.473	.492
	Similarity to category captain	–.204	–.537	.130
Distribution, γ_{3i}	Intercept	.020	–.030	.074
	Category captain	.002	–.151	.154
	Competitive set (excluding private label)	–.087	–.248	.098
	Similarity to private label	**–.249**	–.723	–.049
	Similarity to category captain	**.255**	.050	.599

Notes: We report the upper-level coefficients for β_{8i}, α_{3i}, and γ_{3i}, which correspond to the coefficients of the CC indicator variables in the sales, price, and distribution equations (i.e., Equations 3–5), respectively. LB and UB are the 2.5% and 97.5% quantiles of the estimated parameter's posterior distribution, respectively. Statistically significant values at the 95% level are highlighted in bold.

beyond the CC implementation we study. The rest of this section summarizes our main findings and then discusses their implications for practitioners and researchers. We conclude the article by discussing the limitations of our study.

Three key findings emerge from the CC implementation we study that should be of interest to both practitioners and researchers. First, we find that CC improves category sales in our setting. Despite ample anecdotal evidence on the benefits of CC, our research is the first to empirically document the impact of CC on category performance. We also decompose this impact into the effects of different levers used by category captains in practice (i.e., pricing, assortment, and merchandising). Second, we examine the impact of CC on category stakeholders and find that CC benefits the private label as well as the captain. We expected an increase in private label sales in our setting because one of the opportunities identified in the

FIGURE 5
Change in the Impact of CC on Sales When There Is a Switch from the Current Regime, Which Protects the Private Label, to an Alternative Regime in Which There Is No Private Label Protection



Notes: PL = private label.

captain's SWOT analysis was the potential to improve private label performance. We also expected the increase in the captain's sales because there should be some remuneration for the effort expended to develop and implement a category management strategy. We further find that some competing manufacturers benefit from CC, whereas others suffer. This finding is consistent with the CC literature's mixed predictions regarding the impact of CC on the competing manufacturers.

Third, and most importantly, we examine how product attributes and the retailer's desire to protect the private label affect category performance. Despite the existing literature's predictions regarding the negative impact of the captain's opportunistic behavior, we find that the competing manufacturers that are in direct competition with the captain benefit from CC. However, the competing manufacturers that are in direct competition with the private label suffer from CC because of a decline in their assortment presence. Indeed, we find that the retailer's desire to protect its private label prevents the retailer from maximizing category sales. In particular, private label sales would have decreased but the overall category sales would have increased if the retailer had not protected its private label. We discuss the managerial implications of these findings next.

Managerial Implications

Our study leads to four main managerial insights. First, our analysis reveals that a significant portion of the increase in category sales is due to lower prices. From the retailer's perspective, this finding is important as it illustrates potential perils of using price as a lever. When initiating a CC relationship with a manufacturer, the retailer establishes a collection of performance targets that will be used to assess CC success. Our conversations with category managers indicate that these targets are typically defined in terms of sales rather than profit because retailers are reluctant to release margin information to the captain. Given that sales targets can be achieved by lowering prices in price-sensitive categories, retailers should provide greater specificity in terms of how these targets are to be achieved. Otherwise, the captain may rely heavily on pricing, which is relatively easy to implement but may be costly in the long run because price reductions lower product margins and may heighten consumer sensitivity to price. Improving the assortment, however, is likely more difficult and carries high initial fixed costs, but it should be relatively costless in the long run.

Second, by comparing the pre- and postimplementation sales shown in Table 1, one might conclude that the captain used its authority to adversely influence its competitors. A closer examination of the category dynamics, however, reveals a different story. We find that the manufacturers that closely compete with the captain experience an increase in their assortment presence and sales. The positive impact of CC on the captain's close competitors is in part driven by the retailer's desire to increase category sales by offering a more attractive assortment. Recall that the retailer has a reputation for offering high-quality products. Thus, the captain, which offers premium products, would have had difficulty in justifying the removal of other premium brands (i.e., its close competitors) from the assortment. Moreover, given the retailer's reputation, increasing category sales would have been difficult in the absence of premium brands. These observations suggest that one way for retailers to minimize the risk of opportunistic behavior by the captain is to identify the captain's close competitors and carefully formulate performance objectives so that it is difficult for the captain to justify the removal of those competitors from the assortment.

Third, our analysis sheds light on how private label presence may influence category decisions and performance in the CC context. Consistent with the existing literature (e.g., Ailawadi and Harlam 2004; Ailawadi, Pauwels, and Steenkamp 2008), our findings suggest that there is a delicate balance between pushing the private label and maximizing category performance. On the one hand, solely focusing on category performance may lead to poor private label performance. On the other hand, putting too much emphasis on private label may hurt national brand sales, which in turn negatively affects overall category performance. Thus, retailers should carefully assess the advantages and drawbacks of private label protection prior to working with a captain.

Finally, private label presence has implications for competing manufacturers. The existing literature suggests that private label introduction, which provides affordable product options for consumers, can be beneficial for premium brands but can harm second-tier (i.e., low-price) brands in a category (e.g., Pauwels and Srinivasan 2004). Similarly, we find that the increased presence of the private label after CC hurts the competing manufacturers that are in direct competition with private label. Thus, our findings suggest that offering products that are differentiated from private label in terms of price and product attributes (e.g., package size) can help the competing manufacturers avoid being excluded from the category.

Implications for Researchers

We find that lower prices, a better assortment, and merchandising efforts all contribute to the increase in category sales in our setting. Given the joint importance of all three levers, conclusions drawn from theoretical models, which typically focus on a single lever, should be treated with caution because such models might underestimate the value of CC. Moreover, our findings regarding the negative impact of private label on the competing manufacturers indicate that theoretical studies should not overlook the private label. In particular, the objective functions used in modeling studies, such as revenue and profit maximization, may not fully reflect the retailer's desire to protect its private label. Thus, similar to Chintagunta (2002), defining an objective function that balances private label and category performance may be more appropriate to analyze the advantages and drawbacks of CC initiatives. Our approach of modeling demand substitution on the basis of product attributes also differentiates our study from the existing CC literature. Although similar approaches have been frequently used in the assortment literature (e.g., Fader and Hardie 1996; Rooderkerk, Van Heerde, and Bijmolt 2013), the CC literature uses more stylized models (e.g., linear demand models) to capture demand substitution. Our findings suggest that an attribute-based demand substitution model may lead to more precise inferences on the competitive implications of CC.

Limitations and Future Research

Our article constitutes an important contribution to the literature on CC in large part because the uniqueness of our data set enables us to observe phenomena that have not been previously considered in the CC context. That said, our data set is also limited in a variety of ways, thus creating opportunities for further research.

First, our data set is limited to a single category and retailer. As such, our findings are idiosyncratic to the category, retailer, and the goal of the CC implementation. Further research is needed to test the generalizability of our findings, especially to settings where a retailer seeks to improve category profitability. Moreover, controlling for the retailer's decision to initiate CC through a more comprehensive data set including multiple CC implementations and/or control categories may be useful. This is because our study may overstate the benefits of CC as the CC implementation decision in our context was in part driven by the retailer's relatively poor category performance. It is possible that switching to a CC regime could have a smaller impact in categories that are already performing well.

It is also possible that the relative importance of pricing to assortment as a driver of category sales could differ for mature categories (such as ours) versus categories characterized by product innovation. We expect pricing to play a more important role in settings where the retailer attempts to maximize the sales revenues of a mature category. In contrast, assortment might play a more important role in categories with frequent new product introductions because it might be relatively easy to boost category performance by introducing new products in such categories. In line with these predictions, it would be useful to replicate the models developed herein across many categories and retailers. Such work could yield insights into the boundary conditions of the findings from this article and help researchers and practitioners understand when and under what conditions CC is likely to be most effective.

Second, our data set does not contain information about the products' marginal costs. A richer data set would enable us to study a variety of interesting phenomena, including retailer profitability and consumer welfare implications of CC. Finally, because our data set is limited to a single retailer, it does not enable us to study cross-retailer effects. Prior research has suggested that at least a portion of the sale increase experienced by a manufacturer during a promotion is the result of cross-retailer cannibalization (Van Heerde, Leeflang, and Wittink 2004). Given the right data, it would be worthwhile to consider cross-retailer dynamics that result from CC implementations. This type of research would illuminate the long-term implications of CC, including an understanding of the resulting competitive equilibrium. We hope that our study will pave the way for greater collaboration between retailers and researchers, facilitating further empirical research on CC.

REFERENCES

ACNielsen (2005), *Consumer-Centric Category Management: How to Increase Profits by Managing Categories Based on Consumer Needs*. Hoboken, NJ: John Wiley & Sons.

Ailawadi, Kusum, Eric Bradlow, Michaela Draganska, Vincent Nijs, Robert Rooderkerk, K. Sudhir, et al. (2010), "Empirical Models of Manufacturer-Retailer Interaction: A Review and Agenda for Future Research," *Marketing Letters*, 21 (3), 273–85.

Ailawadi, Kusum, and Bari Harlam (2004), "An Empirical Analysis of the Determinants of Retail Margins: The Role Of Store-Brand Share," *Journal of Marketing*, 68 (January), 147–65.

Ailawadi, Kusum, Koen Pauwels, and Jan-Benedict Steenkamp (2008), "Private-Label Use and Store Loyalty," *Journal of Marketing*, 72 (November), 19–30.

Atalay, Selin, Onur Bodur, and Dina Rasolofoarison (2012), "Shining in the Center: Central Gaze Cascade Effect on Product Choice," *Journal of Consumer Research*, 39 (4), 848–66.

Basuroy, Suman, Murali Mantrala, and Rockney G. Walters (2001), "The Impact of Category Management on Retailer Prices and Performance: Theory and Evidence," *Journal of Marketing*, 65 (October), 16–32.

Besanko, David, Jean-Pierre Dubé, and Sachin Gupta (2005), "Own-Brand and Cross-Brand Retail Pass-Through," *Marketing Science*, 24 (1), 123–37.

Bezawada, Ram, S. Balachander, P.K. Kannan, and Venkatesh Shankar (2009), "Cross-Category Effects of Aisle and Display Placements: A Spatial Modeling Approach and Insights," *Journal of Marketing*, 73 (July), 99–117.

Blattberg, Robert C., and Edward J. Fox (1995), *Category Management: Getting Started, Guide 1*. Washington, DC: Research Department, Food Marketing Institute.

Boatwright, Peter, and Joseph C. Nunes (2001), "Reducing Assortment: An Attribute-Based Approach," *Journal of Marketing*, 65 (July), 50–63.

Borle, Sharad, Peter Boatwright, Joseph Kadane, Joseph C. Nunes, and Shmueli Galit (2005), "The Effect of Product Assortment Changes on Customer Retention," *Marketing Science*, 24 (4), 616–22.

Briesch, Richard, Pradeep K. Chintagunta, and Edward J. Fox (2009), "How Does Assortment Affect Grocery Store Choice?" *Journal of Marketing Research*, 46 (April), 176–89.

Broniarczyk, Susan, Wayne Hoyer, and Leigh McAlister (1998), "Consumers' Perceptions of the Assortment Offered in a Grocery Category: The Impact of Item Reduction," *Journal of Marketing Research*, 35 (May), 166–76.

Carameli, Leo S., Jr. (2004), "The Anti-Competitive Effects and Antitrust Implications of Category Management and Category Captains of Consumer Products," *Chicago-Kent Law Review*, 79, 1313–56.

Chandon, Pierre, Wesley Hutchinson, Eric T. Bradlow, and Scott Young (2009), "Does In-Store Marketing Work? Effects of the Number and Position of Shelf Facings on Brand Attention and Evaluation at the Point of Purchase," *Journal of Marketing*, 73 (November), 1–17.

Chintagunta, Pradeep K. (2002), "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research*, 39 (May), 141–54.

Chintagunta, Pradeep K., Andre Bonfrer, and Inseong Song (2002), "Investigating the Effects of Store-Brand Introduction on Retailer Demand and Pricing Behavior," *Management Science*, 48 (10), 1242–67.

Corstjens, Marcel, and Rajiv Lal (2000), "Building Store Loyalty Through Store Brands," *Journal of Marketing Research*, 37 (August), 281–91.

Desrochers, Debra, Gregory Gundlach, and Albert Foer (2003), "Analysis of Antitrust Challenges to Category Captain Arrangements," *Journal of Public Policy & Marketing*, 22 (Fall), 201–15.

Dhar, Sanjay, Stephen Hoch, and Nanda Kumar (2001), "Effective Category Management Depends on the Role of the Category," *Journal of Retailing*, 77 (2), 165–84.

Drèze, Xavier, Stephen Hoch, and Mary Purk (1994), "Shelf Management and Space Elasticity," *Journal of Retailing*, 70 (4), 301–26.

Du, Rex, Eunkyu Lee, and Richard Staelin (2005), "Bridge, Focus, Attack, or Stimulate: Retail Category Management Strategies with a Store Brand," *Quantitative Marketing and Economics*, 3 (4), 393–418.

Fader, Peter, and Bruce G.S. Hardie (1996), "Modeling Consumer Choice Among SKUs," *Journal of Marketing Research*, 33 (November), 442–52.

Federal Trade Commission (2001), "Report on the Federal Trade Commission Workshop on Slotting Allowances and Other Marketing Practices in the Grocery Industry," (February), https://www.ftc.gov/reports/report-federal-trade-commission-workshop-slotting-allowances-other-marketing-practices.

Federal Trade Commission (2003), "Antitrust and Category Captains Roundtable Discussion," (accessed March 10, 2016), http://www.antitrustinstitute.org/files/270.pdf.

Gelman, Andrew, and Jennifer Hill (2006), *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge, UK: Cambridge University Press.

Gooner, Richard, Neil Morgan, and William Perreault Jr. (2011), "Is Retail Category Management Worth the Effort (and Does a Category Captain Help or Hinder)?" *Journal of Marketing*, 75 (September), 18–33.

Hanssens, Dominique, Leonard Parsons, and Randall Schultz (2003), *Market Response Models: Econometric and Time Series Analysis*, Vol. 12. New York: Springer Science & Business Media.

Hoch, Stephen, Eric Bradlow, and Brian Wansink (1999), "The Variety of an Assortment," *Marketing Science*, 18 (4), 527–46.

Kadiyali, Vrinda, Pradeep K. Chintagunta, and Naufel Vilcassim (2000), "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Investigation of Pricing in a Local Market," *Marketing Science*, 19 (2), 127–48.

Kök, Gürhan, and Marshall Fisher (2007), "Demand Estimation and Assortment Optimization Under Substitution: Methodology and Application," *Operations Research*, 55 (6), 1001–21.

Kumar, Nimalya, and Jan-Benedict Steenkamp (2007), *Private Label Strategy: How to Meet the Store Brand Challenge*. Boston: Harvard Business Press.

Kurtuluş, Mümin, and Alper Nakkas (2011), "Retail Assortment Planning Under Category Captainship," *Manufacturing & Service Operations Management*, 13 (1), 124–42.

Kurtuluş, Mümin, Alper Nakkas, and Sezer Ülkü (2014), "The Value of Category Captainship in the Presence of Manufacturer Competition," *Production and Operations Management*, 23 (3), 420–30.

Kurtuluş, Mümin, and Beril Toktay (2011), "Category Captainship vs. Retailer Category Management Under Limited Retail Shelf Space," *Production and Operations Management*, 20 (1), 47–56.

Kurtuluş, Mümin, Sezer Ülkü, Jeffrey P . Dotson, and Alper Nakkas (2014), "The Impact of Category Captainship on the Breadth and Appeal of a Retailer's Assortment," *Journal of Retailing*, 90 (3), 379–92.

Lilien, Gary, Philip Kotler, and Sridhar Moorthy (1992), *Marketing Models*. New York: Prentice Hall.

Morgan, Neil, Anna Kaleka, and Richard Gooner (2007), "Focal Supplier Opportunism in Supermarket Retailer Category Management," *Journal of Operations Management*, 25 (2), 512–27.

Nijs, Vincent, Kanishka Misra, and Karsten Hansen (2014), "Outsourcing Retail Pricing to a Category Captain: The Role of Information Firewalls," *Marketing Science*, 33 (1), 66–81.

Nowlis, Stephen, Ravi Dhar, and Itamar Simonson (2010), "The Effect of Decision Order on Purchase Quantity Decisions," *Journal of Marketing Research*, 47 (August), 725–37.

Pauwels, Koen, and Shuba Srinivasan (2004), "Who Benefits from Store Brand Entry?" *Marketing Science*, 23 (3), 364–90.

Progressive Grocer (2010), "Smarter, Faster, Stronger," 89 (10), 42–92.

Progressive Grocer (2011), "Collective Excellence," 90 (11), 37–105.

Progressive Grocer (2015), "Winning Game Plans," 94 (11), 36–103.

Progressive Grocer (2016), "Selling Solutions," 95 (11), 41–80.

Rooderkerk, Robert, Harald Van Heerde, and Tammo Bijmolt (2011), "Incorporating Context Effects into a Choice Model," *Journal of Marketing Research*, 48 (August), 767–80.

Rooderkerk, Robert, Harald Van Heerde, and Tammo Bijmolt (2013), "Optimizing Retail Assortments," *Marketing Science*, 32 (5), 699–715.

Rossi, Peter, Greg Allenby, and Rob McCulloch (2005), *Bayesian Statistics and Marketing*. Chichester, UK: John Wiley & Sons.

Subramanian, Upender, Jagmohan Raju, Sanjay Dhar, and Yusong Wang (2010), "Competitive Consequences of Using a Category Captain," *Management Science*, 56 (10), 1739–65.

Van Heerde, Harald, Peter Leeflang, and Dick Wittink (2004), "Decomposing the Sales Promotion Bump with Store Data," *Marketing Science*, 23 (3), 317–34.

Wright, Joshua (2009), "Antitrust Analysis of Category Management: Conwood v United States Tobacco Co.," *Supreme Court Economic Review*, 17 (1), 311–37.

Zenor, Michael (1994), "The Profit Benefits of Category Management," *Journal of Marketing Research*, 31 (May), 202–13.