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Impact of Different Types of In-Store Displays on Consumer Purchase Behavior

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Abstract

Research on consumer in-store shopping behavior does not account for the existence of different types of display locations (e.g. storefront, store rear, secondary, front end cap, rear end cap, and shelf displays). This article focuses on accounting for and understanding the impact of various displays on consumer purchase behavior based on the Stimulus-Organism-Response (SOR) theory. Specifically, we study how displays closer to and farther from the main location of the focal category influence consumer purchase behavior. Furthermore, within the different types of displays we investigate the impact of specific types of displays on consumer's category purchase and brand choice and the moderating role of price and discounts. A hierarchical Bayesian model is estimated using scanner panel data for a large U.S. grocery chain that contains unique information on the number of product facings at multiple display locations within a store. We find that displays closer to the focal category have a larger impact, with front end cap displays having the largest impact on category purchase and shelf displays having the largest impact on brand choice. We also demonstrate the synergistic impact of price and discounts in enhancing the impact of displays on consumer purchase behavior and brand choice. Equipped with these findings we propose a display allocation optimization that results in an average increase in revenue of about 11.15% and a strategy to distribute displays across all locations in the store rather than letting one location dominate.

Keywords: displays, Bayesian hierarchical models, optimization

Introduction

In-store displays are commonplace in retail stores and represent a competitive promotional tool to boost sales. Marketers spend about $60 billion annually in the U.S. on in-store merchandising and shopper marketing with an increase of 8% to 10% every year since 2008 (Tadena 2015). In-store displays draw consumer attention to specific products (Dhar, Hoch, and Kumar 2001) and are often more effective than other standard promotional activities, such as price cuts (Neff 2008). Moreover, with their various locations in a given store (e.g., store front, store rear, shelf, secondary location), different variations of in-store displays exist. These variations influence consumers in different ways. For example, store front displays might encourage impulse buying, while secondary location displays might serve as a reminder or attract attention to a promoted product.

According to a study by Point-of-Purchase Advertising International (2012), more than one in six in-store brand purchases are made when the brand is displayed. Moreover, half the consumers recalled seeing at least one display during their shopping trip, and this recall was not the same across all displays, with floor stands and endcap displays dominating consumers' recall (86% in total). However, retail managers still face a number of challenges in managing in-store displays to improve shopper experience and store performance (Kennedy 2004; Wirespring.com 2016). First, even though it is important, it is difficult to attract consumers' attention and interest to the displayed products in a store as a consumer typically spends 3-7 seconds on the product, termed as the first moment of truth in the industry (Kennedy 2004). Second, store managers lack clarity on the impact of different types of displays and hence are unsure about how to optimally allocate them to increase revenues[1]. This study aims to shed light on the latter issue.

[1] https://www.display.be/POP-14-effective-types-retail-displays.html

Extant research on in-store promotions (Allenby and Ginter 1995; Inman, Winer, and Ferraro 2009; Zhang and Krishnamurthi 2004) has typically combined different types of displays and assessed their overall impact. The practice of combining various types of displays is problematic because of differing levels of visibility (how visible are the displays to shoppers) and exclusivity (the level of devotion or restriction to a particular brand) of displays resulting in differential impact on consumer purchase behavior. For example, Kennedy (1970) shows that display location affects the sales of cigarettes differently, with the highest impact for end-of-aisle displays. While, Breugelmans and Campo (2011) find in an online setting, that store entrance (first screen) and aisle displays outperform shelf tag displays in terms of impact on brand sales. However, the few studies accounting for different displays distinguish only among three broad categories of displays: store entrance, end-of-aisle, and shelf displays. In practice, brick-and-mortar stores have more in-store display types, including store front, store rear, secondary location, front endcap, rear endcap, and shelf. Additionally, there is a lack of understanding on the effectiveness of various displays on consumer purchase behavior and how to optimally allocate these displays across the store.

Based on the Stimulus-Organism-Response (SOR) theory (Donovan and Rossiter 1982; Mehrabian and Russell 1974), our proposed empirical approach involves addressing the following research questions: i) What is the impact of different types of displays, across different locations of the store, on category purchase and brand choice?, ii) Do price and discounts moderate the impact of displays on category purchase and brand choice? and iii) How can the retailer and category captain optimize the number of displays to maximize their revenues? We address the above research questions by accounting for heterogeneity among consumers and endogeneity of various displays, prices, and discounts using a hierarchical Bayes random-effects specification.

We apply our model to a scanner panel data in the soft drinks category from a large U.S. grocery chain. A unique aspect of our data set is the availability of information on six different types of display locations in a store for a one-year period. The six different types of displays in the store include: store front, store rear, secondary location, front end cap, rear end cap, and shelf. When the product is located at a different place from its usual location, such as the display of soft drinks right next to the deli station, the display is coded as secondary location. Front end cap and rear end cap displays are located at either end of a category with the rear end cap being closer to the rear of the store. Displays in in-aisle, mid and side aisle, and in-shelf are treated as shelf displays. We have two pieces of information for each display type in our data: (i) whether a given display type was present in a certain week, and (ii) for each display type the total number of product facings during that week.

Our study provides a number of novel findings. First, we show that at each shopping trip, various displays have differential impacts on consumers' purchase incidence and brand choice behavior. Specifically, all displays have a significant positive impact with displays closer to the main location (aisle) of the focal category having a larger positive impact than displays farther away from the focal category. We find that front end cap displays have the largest and secondary displays have the smallest impact on consumer category purchase incidence. While, shelf displays have the largest impact on consumer brand choice decisions. Second, we demonstrate the synergistic role of price and discounts in enhancing the impact of displays on category purchase incidence and brand choice. The moderating role of price and price discounts is the strongest for the impact of front end cap and shelf displays on category purchase and brand choice, respectively. Next, using elasticity calculations we demonstrate the relative impacts of each of the displays on purchase incidence and brand choice probabilities. The usefulness of our approach to retailers is further explored using an optimization exercise, wherein we propose the optimum number of product facings for displays that will help the retailer and category captain increase their revenues. We find that the strategy of the largest market share brand having the largest number of product facings in displays turns out to be detrimental in terms of the revenue to the retailer. In addition, contrary to the current practice, we find that a good strategy is to distribute the displays across all the locations of the store resulting in an average increase of 11.15% in retailer revenue. Finally, we also discuss optimal strategies for a category captain to increase their revenues through display allocation across the store.

This research contributes to retailing literature in significant ways. The differential impacts of the number of product facings at various in-store display locations are captured by the size and signs of main and interaction effects between displays and between displays and other marketing variables. Furthermore, we find some display locations are detrimental for brand choice, as they signal the product category displayed but the initiated purchase can lead to consumers buying other brands. Equipped with these findings, we provide new insights into the effectiveness of various display locations in a store to help retail managers make optimal display decisions in a product category to increase revenue. One critical issue retail managers grapple with is the effectiveness of each display type. Our results aim to provide managers with success metrics on historically displayed promotions that can aid in future decision making.

Background literature

In-store displays are marketing activities in which the product receives special placement at a retailer, in addition to or instead of its usual store location (Nielsen 2013). The main aim of in-store displays is to attract shoppers' attention. The role of displays, in driving impulse buying and brand switching, becomes even more prominent in fast-moving consumer packaged goods wherein a significant amount of purchases is unplanned (Drèze, Hoch, and Purk 1995; Inman, Winer, and Ferraro 2009). A study conducted by Ogilvy Action found that almost 60% of the shoppers made their purchase decisions in the store, and 24% of these purchases were influenced by in-store displays (Neff 2008). Moreover, this study showed that displays had a significant impact even without providing a price discount. Given the substantial importance of in-store displays, however, research investigating the impact and effectiveness of various types of displays is rare (Bemmaor and Mouchoux 1991).

One important issue retailers grapple with is the effectiveness of different types of displays. Traditionally, store location is used as a way to characterize different types of displays (Tellis 1998). Therefore, in this study, we classify displays into six major types: store front, store rear, secondary location, front endcap, rear endcap, and shelf. As we discuss in the conceptual framework section, these various displays should influence consumers in different ways. Prior research, however, does not take different types of displays into consideration and combines them into one display variable (Allenby and Ginter 1995; Anderson and Simester 1998, 2001). In addition, research on choice models incorporates displays as dummy variables (Bemmaor and Mouchoux 1991; Lee, Kim, and Allenby 2013; Villas-Boas and Winer 1999) or treats them as control variables resulting in relatively less attention toward the effects (Bell, Corsten, and Knox 2011; Gupta 1988; Yang, Chen, and Allenby 2003). This is problematic because if various display locations have differential impacts on consumer purchase decisions, combining them into a dummy variable would provide an inaccurate and biased view of their effectiveness (Breugelmans and Campo 2011; Tellis 1998). Chandon et al. (2009) investigate the differential impact of displays in an experimental setting, but the location is only on a shelf rather than the entire store. Similarly, Breugelmans and Campo (2011) compare the effects of multiple types of displays only in a virtual environment and not in a physical store (where a consumer's physical effort for shopping and the size and location exclusivity of displays matter). We empirically and comprehensively examine the role of a broad range of displays (i.e., store front, store rear, front endcap, rear endcap, shelf, and secondary location) in a physical retail store setting. In doing so, we aim to extend the retailing literature by investigating the impact of different types of displays on consumer purchase decisions using secondary data. Table 1 provides a summary of the relevant literature and highlights our contributions.

-- Insert Table 1 here --

Conceptual Framework

We first discuss the physical and theoretical differences across the different types of retail displays. Then we adopt the SOR theory (Donovan and Rossiter 1982; Mehrabian and Russell 1974) to examine how various displays in different locations influence consumers' category purchase incidence and brand choices, and propose a number of hypotheses.

Characteristics of Different Displays

The six in-store displays are classified based on their different locations in the store. We can broadly classify these displays based on their proximity to the main location (aisle) of the focal product category in the store: displays farther from the focal category (store front, store rear, and secondary) and displays closer to the focal category (front cap, rear cap, and shelf), consistent with prior research (e.g., Breugelmans and Campo 2011; Hui et al. 2013). We first discuss displays farther from the focal category. Storefront displays are placed in the front area of a store to attract consumers' attention and interest in the displayed product category or brand, or to induce impulse purchase. Compared to store front, store rear area is more focused on in-store navigation from one aisle to another, so it is more likely to be packed with shoppers. In addition, in most cases, store rear is occupied with products on sale from multiple categories that could create a clutter. Thus, store rear displays might not be easily noticeable. Secondary displays are usually placed next to a related product category such as soft drinks displayed at a deli corner or checkout counter.

For displays closer to the focal category, when consumers navigate an aisle of products where shelf displays are located, they are likely to make a purchase as they can easily evaluate different attributes of multiple brands. Front and rear endcap displays are interesting locations as they can be considered as the starting or ending point of an aisle and the products displayed at these locations could potentially influence shoppers' brand purchase intentions.

To understand the similarities and differences across different displays, we summarize the various (physical, content, and theoretical) characteristics of the six store displays in Table 2. The six displays differ in terms of location, proximity to the focal category, size of displayed area, focus on a brand or category, and contents such as size of fixtures, shape, color, material, information content, and price promotion. Specifically, due to the different locations, store front displays typically have a large size with many product facings and detailed information on the products, and a focus on promoting the product category or brand purchase (potentially impulse purchases) with price promotion for a particular brand or a number of brands in the same category. As a result, the color of such displays matches that of the product category or brand, their shapes are usually in bins, cases or windows, and materials used tend to be cardboard, wood, metal or plastics. Store rear displays and secondary displays are located in the rear or other open areas in the store, respectively. They are large- or medium-sized with detailed information on displayed products. Their focus tends to be either category or brand related with associated price discounts. As a result, the color, shape and material are varied. In contrast, front endcap and rear endcap displays are located at the front or rear end of a category aisle, respectively. Their spaces at the ends of an aisle are relatively constrained with limited product facings and the use of wood or metal materials, resulting in a medium-sized display with a medium level of information on displayed products. Endcap displays usually focus on promoting a particular brand in a category with a brand-specific price promotion. Hence, their colors usually match the color of the displayed brand. Lastly, shelf displays are usually large gondolas spanning several shelves with many product facings, and provide extensive information on the promoted brand or product in order to signal a deal or make the brand stand out among multiple competing brands in the shelf. As a result, it usually focuses on highlighting a specific brand with a brand-level price promotion. Its color matches the promoted brand. Shelf displays are typically large in size and made of metal, wood, cardboard or plastics.

-- Insert Table 2 here --

The differences in the physical characteristics of the six displays lead to interesting differences in the theoretical characteristics of these displays. Specifically, displays farther from the focal category like store front displays are usually aimed at increasing category or brand purchase with brand- or product category-oriented price discounts. Store rear and secondary displays focus on either category or brand purchases with category- or brand-oriented deals. While, displays closer to the focal category, endcap (both front and rear) and shelf displays tend to highlight brand purchases with price discounts focused on a specific brand. As a result, based on how a display is exclusively devoted to a brand, shelf displays have the highest exclusivity (the level of devotion or restriction to a particular brand), followed by endcap (front and rear) displays, then secondary and store rear displays, and finally the storefront displays have the lowest exclusivity. Given the locational differences, storefront displays are ranked the highest in terms of accessibility (how accessible it is to consumers) and visibility (how visible to consumers) to consumers, followed by secondary and front endcap displays, then by store rear and rear endcap displays. Shelf displays have the lowest accessibility and visibility due to their locations in a shelf inside a category-specific aisle. Due to their informational content differences, the informativeness (the amount of information) of the displays also varies, with storefront, store rear and secondary displays with larger sizes tending to be highly informative, followed by endcap displays, and then by shelf displays.

Conceptual Framework and Hypotheses

We develop our conceptual framework, shown in Figure 1, by adopting the SOR theory and examining the impact of in-store displays on category purchase incidence and brand choices. SOR theory suggests that an environmental stimulus S influences consumers' internal cognitive or affective states O, which then affect their response behavior R (Mehrabian and Russell 1974). This theory has been widely used in marketing to study the influence of offline retail atmospheric cues on consumer responses (Mattila and Wirtz 2001; Parsons 2011) and the impact of online stores' atmospheric stimuli on consumer browsing and purchase behaviors (Ding, Li and Chatterjee 2015; Eroglu, Machleit and Davis 2001).

-- Insert Figure 1 here --

We assert that retail environmental stimuli affect the consumers' cognitive states (attention and information processing), prompting approach and avoidance behaviors (e.g., Baker et al. 1992; Bitner 1992; Spangenberg, Crowley and Henderson 1996). Approach behaviors entail positive actions, such as intentions to stay or explore, directed toward a particular setting;

avoidance behaviors are the opposite (Sherman and Smith 1987). Specifically, via the effects of various displays on the unobserved customer cognitive states (Organism), we examine which displays (Stimulus) in a store are more effective at attracting consumers to make product category and brand purchases (Response). Given the large number of displays, we first discuss the impact of displays that are farther versus closer to the focal category. We subsequently hypothesize the impact of various displays within each of these two groups. Finally, we discuss the moderating role of product price and discount on the impact of displays on purchase incidence and brand choice.

As shown in Figure 1, for the stimulus, we focus on the six types of store displays, broadly classified into two groups based on their proximity to the main location of the focal category, in a retail store. We are interested in how various displays in different locations, acting as stimuli, influence customer category and brand purchase behavior. As discussed in previous research (East, Eftichiadou, and Williamson 2003; Larson, Bradlow, and Fader 2005, Breugelmans and Campo 2011), different areas in a store may trigger different mindsets or cognitive states for consumers. Thus, for the organism part of the theory, we consider customers' cognitive (attention and information processing) states because it has been shown to be an important mechanism for the impact of retail atmospheric cues on consumer attitudes and purchase behaviors in a store (Bitner 1992; Spangenberg, Crowley and Henderson 1996). In addition, impact of displays in mature consumer packaged goods categories, where consumers shop using mental or shopping lists, is more likely driven by cognitive and information processing[2] (attention to displays) rather than emotional or affective responses. Specifically, research has demonstrated how spacious appearances create better image and cognitive

[2] We would like to thank an anonymous reviewer for pointing this out.

impressions and therefore increase cognitive satisfaction (Lam et al. 2011). Therefore, for the organism part in the conceptual framework, we focus on customers' cognitive (attention and information processing) states. Thus, in-store displays with their strategic placements, exclusivity, and creativities like layout and size play a critical role in grabbing consumer attention by highlighting various aspects that are important in information assimilation and processing external cues like prices and promotions. Finally, for the response component, we examine a two-stage model of consumer shopping process including category purchase incidence and brand choices. As a result, we allow various displays and other stimuli variables to have a differential impact on consumer category incidence and brand purchase.

Proximity to the focal category: The main role of in-store displays is to capture consumers' attention and induce category or brand purchases with or without other marketing activities such as price discounts. Previous research on promotions and in-store shopping behavior has demonstrated a positive effect of displays in brick-and-mortar and online stores (e.g., Breugelmans and Campo 2011) while also enhancing shoppers' approach behavior toward the product (Fiore, Yah, and Yoh 2000). Thus, we expect a positive influence of in-store displays on product category incidence across all locations. However, as shown in Table 2, different displays have differing levels of accessibility, visibility, informativeness, and proximity to the focal category, and hence we expect differences in its impact on category purchase incidence and brand choice. We believe that proximity of displays to the focal category should have a significant difference in terms of how consumers assimilate information in their cognitive states. This is because the placement of displays across different locations has been demonstrated to offer goal-oriented shoppers several advantages (Bezawada et al. 2009) like reduced information search complexity, reduced acquisition efforts, and cueing of underlying needs (Ratneshwar, Pechmann, and Shocker 1996), resulting in greater information assimilation and cognitive processing, similar to information processing from external cues such as brand advertisements (MacInnis et al. 1991). Research on information processing (Chandy et al. 2001; MacInnis and Jaworski 1989) suggests the existence of multiple stages of information processing and the differential impact of each state on consumers' responses and attitudes toward advertisements and brands. Using consumer involvement theory (Greenwald and Leavitt 1984), consumers' information states for in-store displays can be broadly classified into two categories—attention and pre-attention (seeing but not paying attention to displays). The presence of different displays at various locations in a store would elicit different levels of attention that could in turn result in the differential impact of displays on purchase behavior.

Thus, displays closer to the focal product category (front cap, rear cap, and shelf) should have a larger impact, due to greater attention and processing in consumers' cognitive states, for shoppers interested in the focal category compared to displays farther away (storefront, store rear, and secondary location). Displays closer to the focal product category would provide shoppers more brand options as they can venture into the category aisle due to its proximity. However, for displays farther away from the focal category the number of options available would be limited, leading to lower attention in consumers' cognitive states, and hence lower responses or lower purchase incidence and brand choice probability. Furthermore, displays closer to the focal product category have much higher exclusivity than displays farther away from the focal product category leading to a higher probability of being noticed. Therefore, we have

H1: Displays closer to the focal category have a greater positive impact on purchase incidence and brand choice than displays farther from the focal category.

Impact of Specific Displays on Category Purchase Incidence: As shown in Table 2, among the displays closer to the focal category, front end cap has the highest accessibility, visibility and exclusivity, closely followed by shelf displays and finally by rear end cap displays. Furthermore, front end cap and shelf displays are larger in size than rear end cap, as they usually occupy an entire shelf at the entrance and within the category aisle, respectively, as opposed to rear end cap displays which are usually much smaller with fewer product facings and limited space allocated. In addition, the focus of the end caps (front and rear end cap) is different from shelf displays with the latter predominantly emphasizing a specific brand. Thus, end cap displays should have a greater impact on consumer attention in attracting and highlighting specific categories in a cluttered retail store, resulting in a greater positive effect on consumer category purchase decisions compared to shelf displays. This is especially true since shelf displays require consumers to be already in the focal category to be noticed. In addition, given the higher accessibility and exclusivity of front end cap compared to rear end cap, we, expect front end cap to have a larger impact on category purchase than rear end cap. The effects of front end caps on category incidence are followed by rear end cap, and shelf displays due to their decreasing visibility, informativeness and accessibility to consumers, and hence lower attention and information processing in consumers' cognitive states.

For displays farther from the focal category, storefront displays with the highest accessibility, visibility and informativeness are more likely to be aimed at increasing consumer category incidence compared to store rear and secondary displays. As a result of in-store stimuli to consumers, storefront displays may have a higher probability of attracting consumer attention and engagement potentially leading to higher probability of category purchase incidence (Baker 1986; Bitner 1992) compared to store rear and secondary displays. The effects of storefront displays on category incidence are followed by secondary, and store rear displays due to their decreasing visibility, exclusivity and accessibility to consumers, and hence lower attention and information processing in consumers' cognitive states. Therefore, we have

H2 (a): Front end caps have stronger positive impact on category purchase incidence followed by rear end cap and shelf displays.

H2 (b): Store front displays have stronger positive impact on category purchase incidence than store rear or secondary displays.

Impact of Specific Displays on Brand choice: For consumer brand choices, however, we expect the impact of displays to be different than for category purchase incidence. For displays closer to the focal product category, shelf displays have the highest exclusivity to a particular brand, usually with brand-oriented price promotion, so we expect shelf displays as store stimuli to have the strongest positive impact on brand choice. Shelf displays attract customer attention to a branded product (Chandon et al. 2009), when the customers are already in the category, with an intention to purchase, resulting in higher attention in their cognitive states and an approach behavior with the largest probability of brand purchase. The larger impact of shelf display is followed by endcap (front and rear) due to their exclusivity and proximity to the focal category.

For displays farther from the focal category, secondary displays are aimed at focusing on specific brands and inducing impulse purchase of specific brands arising mainly due to information regarding favorable prices (Bell, Corsten, and Knox 2011). This is followed by storefront and store rear displays as they are mainly aimed towards the category with a low probability of focusing on specific brands. Storefront and store rear displays have decreasing exclusivity and brand focus, and hence declining attention levels of consumers with lower brand choice probabilities. Therefore, we have hypothesized

H3 (a): Shelf displays have stronger positive impact on consumer brand choice compared to front or rear end cap displays.

H3 (b): Secondary displays have stronger positive impact on consumer brand choice than store front or store rear displays.

Moderating role of price and promotion: Since in-store displays usually include information on product price and/or promotion in order to encourage product category or brand purchase (Zhang 2006), it is important to disentangle these two effects (the display effect vs. price/price promotion effect). Therefore, in addition to controlling for the impact of price and price promotion, we further investigate how product price and price promotion moderate the influence of various in-store displays. Given the positive main effect of displays on category incidence and brand choice, a lower product price or a deeper price promotion in a display is more likely to attract consumer attention and increase their information processing, leading to a positive moderating impact of price or price promotion on consumer category incidence and brand choices (e.g., Bucklin and Lattin 1991; Papatla and Krishnamurthi 1996). Further, such a moderating effect of price and price promotion on category incidence will be the strongest for products in end cap displays due to their proximity to the focal category along with higher visibility, exclusivity and accessibility which contribute to grabbing consumers' attention in their cognitive states. Additionally, front end cap displays have greater accessibility and visibility compared to rear end cap. Thus, we expect the strongest positive moderating role of price and promotion on the impact of front end cap on category purchase incidence. In contrast, due to the very high exclusivity to a particular brand for shelf displays as in-store stimuli, compared to all other displays, we expect the strongest positive moderating role of price and price promotion on the impact of shelf displays on brand choice. Therefore, we hypothesize

H4: Price and price promotion positively moderate the impact of displays, with the largest impact for front end caps, on product category incidence.

H5: Price and price promotion positively moderate the impact of displays, with the largest impact for shelf display, on brand choice.

Model Development

The Purchase Incidence: Binary Nested Logit

We assume a consumer's decisions of purchase incidence and brand choice are dependent through a nested logit structure. First, the probability $P_{it}(inc)$ that household *i* purchases in a product category at shopping trip *t* is specified as:

$$(1)\quad P_{it}(inc) = \frac{\exp(\beta_{0i} + \beta_{1i}X_{1t} + \beta_{2i}X_{2it} + \beta_{3i}X_{3t} + \beta_{4i}IV_{it} + \xi_t)}{1 + \exp(\beta_{0i} + \beta_{1i}X_{1t} + \beta_{2i}X_{2it} + \beta_{3i}X_{3t} + \beta_{4i}IV_{it} + \xi_t)}.$$

The elements of X_{1t} are the key marketing variables such as the number of product facings at different display locations[3], price promotion, and price, and the two-way interactions between various displays and between displays and price promotion/price. X_{2it} consists of consumers' purchase behavior related variables such as recency, past purchase frequency, a dummy for the category purchase at the last shopping trip, and purchase quantity during the initialization period. X_{3t} is a vector of control variables such as seasonality of category purchase or specific events. The nested logit structure is incorporated by having the inclusive value, IV_{it}, and is given by,

$$(2)\quad IV_{it} = \ln \sum_j \exp(V_{ijt})$$

[3] Our data has information about various display locations (i.e. store front, store rear etc.) but not for other characteristics (like informativeness, accessibility or visibility). With access to appropriate data these additional characteristics can be easily incorporated in our model and we leave this as an avenue for future research.

where V_{ijt} is the deterministic utility of the brand choice probability (Ben-Akiva and Lerman 1985). Lastly, ξ_t is an unobserved demand shock that leads to potential endogeneity of displays, price, and price discounts.

The Brand Choice: Binary Logit

The brand choice probability, $P_{it}(\text{j} \mid inc)$ that household *i* purchases a brand *j* at shopping trip *t* given a decision to purchase in the product category, is expressed by a binary logit model as described below.

$$(3)\quad P_{it}(\text{j} \mid inc) = \frac{\exp(\gamma_{0ij} + \gamma_{1i}W_{1jt} + \gamma_{2i}W_{2jt} + \gamma_{3i}W_{3t} + \xi_{jt})}{1 + \exp(\gamma_{0ij} + \gamma_{1i}W_{1jt} + \gamma_{2i}W_{2jt} + \gamma_{3i}W_{3t} + \xi_{jt})}$$

W_{1jt} consists of marketing activities such as the number of product facings in different displays, price promotion, and price, and the two-way interactions of the marketing variables. Elements of W_{2jt} include a dummy for brand loyalty and variables capturing competition from multiple brands that could be displayed at the same or different locations during a given shopping trip. The last vector, W_{3t}, is for control variables similar to the purchase incidence model. ξ_{jt} is an unobserved demand shock related to the endogeneity specification that is discussed later.

Individual Heterogeneity

We incorporate individual heterogeneity in parameters in both purchase incidence and brand choice models. The vector of individual parameters θ_i is specified as:

$$(4)\quad \theta_i = \{\beta_{0i}, \beta_{1i}, \beta_{2i}, \beta_{3i}, \beta_{4i}, \gamma_{0ij}, \gamma_{1i}, \gamma_{2i}, \gamma_{3i}\}$$

Heterogeneity across individuals is captured by a hierarchical Bayes random-effects model (Allenby and Ginter 1995), given by,

$$(5)\ \theta_i = \Delta Z_i + \zeta_i$$

where Z_i is the vector of demographic covariates (age, income, and household size) that account for observed heterogeneity and ζ_i is the unobserved heterogeneity among individuals and is assumed to be multivariate normal $(0, \Sigma_\zeta)$.

Endogeneity of Marketing Variables

Displays and other marketing activities, such as prices and discounts, may be determined by factors (e.g., competition from other stores) unobserved by researchers but observed by retailers, and may be correlated with the demand shock in the purchase incidence utility (ξ_t in Equation 1) and the brand choice utility (ξ_{jt} in Equation 3). As a result, retailers may set prices, discounts and determine display locations endogenously. Therefore, we assume that the number of product facings in displays, the mean price and discount in a focal product category are endogenous and use an instrumental variable specification to account for it (e.g., Villas-Boas and Winer 1999). Since marketing variables like price are not customized at the individual consumer level and its endogeneity is likely caused by unobserved competitive and environmental factors, its lagged term has been shown to be a good instrument in retail settings to account for their potential endogeneity (Villas-Boas and Winer 1999; Yang et al. 2003).

Specifically, for the instruments for the number of product facings in displays, we use the lag of the number of product facings in displays in a given product category at each location at time *t-1*. The number of displays from the previous period might influence the number of displays in the current period due to inertia of making drastic changes in a store from week to week. However, the number of product facings in displays from the previous period, is less likely to directly influence the consumer's purchase utility in the current period. Similarly, we use average sticker price per ounce and average discount per ounce in the previous period as the instruments for price and discount in the current period. We specify display, average price per ounce and discount at time *t* as follows:

$$(6)\ \ DISP_{djt} = \eta_{0dj} + \eta_{1dj} DISP_{dj,t-1} + \kappa_{djt}$$

$$(7)\ \ DISC_{jt} = \lambda_{0j} + \lambda_{1j} DISC_{j,t-1} + \mu_{jt}$$

$$(8)\ \ PRICE_{jt} = \nu_{0j} + \nu_{1j} PRICE_{j,t-1} + \pi_{jt}$$

where the coefficients η_{0jd} and η_{1jd} are display-specific[4]. The error terms of display (κ_{djt}, d = 1, …, D, where D is the number of different types of display and j = 1, …, J), price discount (μ_{jt}, j = 1, …, J), and price (π_{jt}, j = 1, …, J) equations indicate possible shocks from the supply side and the vector of common demand shocks of purchase incidence (ξ_t in Equation 1) and brand choice probability (ξ_{jt} in Equation 3) models. The error terms follow a multivariate normal distribution with mean zero and the variance-covariance matrix Σ. The off-diagonal terms of the variance-covariance matrix Σ associated with purchase incidence and brand choice models indicate the interdependence structure across purchase incidence and brand choice and the multivariate nature of brand choice probabilities.

The proposed model is estimated with Bayesian MCMC method and the estimation algorithm is provided in Web Appendix A. Model comparison and robustness checks, and estimation results for endogeneity are presented in Web Appendices B and C, respectively.

Data Description and Model Free Evidence

The scanner panel data for our empirical approach comes from a large U.S. grocery chain. The data contain transaction history of membership card holders for 42 weeks (t = 1, …, 42), from August 2012 to August 2013. We use the first six weeks of data to initialize some of

[4] In order to avoid duplication, we used DISP in Equation 6 instead of the specific names of multiple displays.

the variables like recency, frequency and monetary value. Household-specific information for each transaction includes purchase quantity, brands purchased, and marketing activities such as price, price discount, feature advertisements, and displays. The six different types of displays in the store include: store front, store rear, secondary location, front end cap, rear end cap, and shelf. For each display type in our data, we have information about its presence in a certain week and the total number of product facings for the display type during that week.

We chose the soft drink category because it has a large number of different types of displays. Furthermore, there were only four large brands: Coke, Pepsi, Dr. Pepper, and private brand that accounted for 98.5% of the total transactions (26,243) in a given store and 99.9% of the total number of displays for soft drinks in the store. The market share of each brand among the four is respectively 33.8% (Coke), 30.6% (Pepsi), 17.8% (Dr. Pepper), and 17.8% (Private brand). We used 500 randomly selected households for parameter estimation and 200 different households as the holdout sample[5]. Tables 3 and 4 provide the variable specification and summary statistics for the variables in our data set, respectively.

--- Insert Tables 3 and 4 here ---

To show the potential differential impact of different displays on purchase behavior, we plot the numbers of weekly category purchases and the six types of displays over time in Figure 2. Figure 2A provides the number of weekly purchases while Figures 2B and 2C provide information on the number of product facings across the six displays - store front, store rear, secondary location, front cap displays, rear cap, and shelf. According to these figures, different displays exhibit very different dynamic patterns over time. There is a great deal of temporal variation in the number of weekly purchases of soft drinks that is largely correlated with the

[5] In addition to the cross sectional holdout sample, we also did within-household split and hold out for the last five weeks for each household. We obtained similar model comparison results.

dynamics of storefront, front endcap, secondary location and shelf displays. Further, we divide the one-year data into four quarters and compute the correlations between the number of category purchases and the numbers of product facings in the six different types of displays. Table 5 shows the results. It is clear that the correlations between various displays and category purchases are very different with front endcap and store front displays for soft drinks having the highest overall correlations. Therefore, it is important to examine the differential impact of different displays on shoppers' transactions. In addition, this evidence does highlight the need for an empirical model that captures multiple components such as cross-sectional consumer heterogeneity, impacts of other covariates and brand-level effects of displays.

--- Insert Table 5 and Figure 2 here ---

Variable Description

The utility in the purchase incidence model (Equation 1) is dependent on a vector of marketing activities (X_{1t}), consumers' purchase behavior (X_{2it}), and control variables (X_{3t}).The vector X_{1t} includes the total number of facings of soft drink products displayed in the store front ($STFR_{t}$,), store rear ($STRR_{t}$), secondary locations ($SCDR_{t}$), front endcap ($FCAP_{t}$), rear endcap ($RCAP_{t}$), and shelf ($SHELF_{t}$). Other marketing variables like average price discount ($DISC_{t}$) and sticker price per ounce ($PRICE_{t}$) and two-way interactions between marketing activity variables are also a part of X_{1t}.

For consumers' purchase behavior-related variables in X_{2t} , we measure recency (Cat_REC_{i}), frequency (Cat_FREQ_{i}), and monetary value (Cat_MNTR_{i}) for consumer *i* in the given product category. It also includes the number of feature advertisements ($NFEAT_{t-1}$), a dummy (LP_{it}) that equals 1 if the category is purchased in the last shopping trip of household *i* to capture state dependence, and a mean-centered purchase quantity (LQ_{it}) from all past purchases for a given household (Zhang and Krishnamurthi 2004).

The vector X_{3t} consists of a possible competition in displays and two control variables. Since multiple product categories are likely to be displayed at the same location such as store front, the possible cross-category competition is captured by three variables: the number of product facings in secondary displays ($SCDROT_t$), store front displays ($STFROT_t$), and store rear displays ($STFROT_t$) of other product categories. Next, X_{3t} includes an event dummy (EVENT) that equals 1 if the transaction occurs in the week of the Super Bowl, NCAA tournament games, and Independence Day to control for seasonality in sales of soft drinks. The last variable in X_{3t} is a first-week dummy (FWEEK) that equals 1 if the transaction occurs in the first week of February and June, to control for missing transactions in January and May.

Similarly, the vector of the key marketing activity variables in the brand choice probability (W_{1jt} in equation 6) includes: six variables for the number of facings of soft drink products for various displays ($STFR_{jt}$, $STRR_{jt}$, $SCDR_{jt}$, $FCAP_{jt}$, $RCAP_{jt}$, $SHELF_{jt}$), the sticker price ($PRICE_{jt}$) and price discount ($DISC_{jt}$) per ounce of brand *j*. The first variable in W_{2jt} is a dummy for the last brand purchased accounting for a consumer's brand loyalty (LB_{ijt}). Next, to account for possible competition across brands for a limited space, the number of competitors of brand *j* that have displays in the same location ($COMPS_{jt}$) and different locations ($COMPD_{jt}$) from brand *j* are included in W_{2jt}. Lastly, EVENT and FWEEK dummy are the elements of W_{3t} included as control variables.

For the covariates in vector Z_i (Equation 5), which models individual heterogeneity, we use income level, age, and number of household members for consumer *i*. As discussed previously, we use the lagged number for the six displays, price discount, and price as instruments to account for endogeneity in Equations 6-8.

Estimation Results

Parameter Estimates for Purchase Incidence

Table 6 provides the estimation results for the purchase incidence model. First, for the main effect of various displays, we find full support for H1, H2(a), and H2(b). Specifically, end cap displays show the strongest influence on purchase incidence (0.434 for front end cap; 0.353 for rear end cap), followed by shelf displays (0.346) and store front displays (0.179). Secondary displays and store rear displays do not affect purchase incidence significantly. The stronger effect size of displays closer to the focal category (end cap and shelf displays) than displays farther from the focal category (store front, store rear, and secondary) is consistent with H1. Among displays closer to the focal category, front end cap displays have a stronger effect than rear end cap and shelf displays, as hypothesized in H2(a). Also, H2(b) is confirmed due to the positive effect of store front displays and insignificant effects of store rear and secondary displays. Along with displays, other marketing variables, price promotion (0.59) and price (-0.293), significantly influence purchase incidence.

The interactions between price and display locations and between price promotion and display locations support H4. When price and price discounts are offered, the positive effects of in-store displays are enhanced and the magnitude of the effects is different across display locations. Furthermore, the moderating effect of price and price discounts turn out to be the strongest for front end cap displays (interaction effects with price and price discount are 0.527 and 0.65, respectively), followed by rear end cap displays (price: 0.516; price discount: 0.547), shelf displays (price: 0.414; price discount: 0.503) and store front displays (price: 0.123; price discount: 0.271).

We also find significant interactions between various displays, which could guide the most effective way of displaying merchandise at multiple locations. Among the 15 two-way interactions, end cap displays enhance the effect of other display locations (0.24~1.841). When merchandise is displayed at front end cap and shelf locations (1.841) and rear end cap and shelf locations (1.574), the effects turn out to be the strongest, followed by front end cap and rear end cap displays (1.179) and store front and front end cap displays (0.918). As consumers navigate near the focal category, front end cap displays can increase the visibility and accessibility of the category and the effect becomes more pronounced when the category is also displayed at another highly visible and a must-visit location, the store front. This is also true when shoppers step inside a highly exclusive location, the shelf, with an increased willingness to buy.

Consumers' previous purchase behavior, recency (-0.379), frequency (-0.46), monetary value spent on the product category (-0.225), and the purchase quantity during the previous shopping trip (0.281) show significant influence as well as positive loyalty toward the product category (0.295) as expected. Finally, we find significant competition across product categories, in that the number of other categories displayed at non-exclusive locations like storefront (-0.313) and store rear (-0.412) have negative impact on purchase incidence of the focal category.

-- Insert Table 6 here --

Parameter Estimates for Brand Choice

Table 7 shows the parameters for the brand choice model. Out of the six displays, the three strongest effects on brand choice probability come from shelf displays (1.195), front end cap (0.811), and rear end cap (0.775). The magnitude and order of the effects confirm H1 and

H3(a). However, H3(b) is not supported as storefront displays turn out to have a stronger effect (0.434) than store rear displays (-0.195) and the effect from secondary displays is not significant. The former may be due to the occasional brand-oriented promotions and focus on storefront displays used by the retailer. Overall, frequently visited and visible area inside the store and the most exclusive area for the product category strongly influence consumers' brand choice, whereas areas that are accessible but also used for other purposes (e.g., grabbing a cart and sanitizing hands) are less effective. The insignificant effect of secondary displays could be because the location is often hard to be associated with the focal category and due to the relatively small size of such displays than storefront. Moreover, store rear displays have a negative effect on the brand choice, showing that the low exclusivity and the relatively low accessibility of the location hurts the displayed brand.

Similar to the purchase incidence, the effect of product displays become stronger when combined with price or price discount. The moderation effect is positive and is the largest for shelf displays (interactions with price: 0.974; price discount: 0.563), followed by end cap displays (interactions with price: 0.962 for front end cap and 0.703 for rear end cap; price discount: 0.46 for front end cap and 0.451 for rear end cap). The result strongly supports H5. In addition, the positive moderation effect is also observed for displays farther from the focal category, where storefront displays are influenced more (interactions with price: 0.276; price discount: 0.269) than secondary displays (interactions with price: 0.178; price discount: 0.227) and store rear (interactions with price: 0.125; price discount: n.s.).

The two-way interactions between displays at different locations show the possible effective ways of merchandising a product category across various areas in the store. When multiple locations of displays involve displays closer to the focal category, the impact is positive on the brand choice in most cases (0.199~1.001). The highest effect is observed when end caps and shelf displays are combined (0.701~1.001). The convenience and accessibility of end caps and exclusivity of shelf displays possibly leads to the synergistic effects.

Lastly, we also find a positive effect of brand-specific loyalty (0.333), and a negative impact of competition across brands that are displayed at the same location (-0.363), and a significant effect of big sports events and holidays (0.555).

-- Insert Table 7 here --

Investigating Display Effectiveness and Optimal Allocation

We conduct two simulations that can aid retail managers and deepen our understanding of display effectiveness across locations and brands. First, we calculate the impact of 1% increase in price, discounts, and the number of product facings in each display across locations (i.e., elasticity) on purchase incidence of the category and brand choice probabilities for the four brands. This helps us investigate the effectiveness of each marketing activity for each brand. Second, given the geographic constraints in a retail store, we propose and find the optimal number of product facings in displays that can be allocated for each display type while maximizing retailer or category captain's revenues.

Elasticities of Marketing Variables

We compute own and cross elasticities of price, discounts, and displays across six locations for purchase incidence and for brand choice. The elasticity e^s for purchase incidence and the elasticity e_j^s for brand j, are obtained as:

$$e^s = \sum_{i=1}^{N} P_i^{*MKT}(inc) - \sum_{i=1}^{N} P_i^{MKT}(inc) \quad (9)$$

$$e_j^s = \sum_{i=1}^{N} P_i^{*MKT_k}(j \mid inc) - \sum_{i=1}^{N} P_i^{MKT_k}(j \mid inc) \quad (10)$$

where $P_i^{MKT}(inc)$ = purchase incidence probability.

$P_i^{*MKT}(inc)$ = purchase incidence probability for a 1% increase in a marketing variable for brand *k, k* = {1,…, J}, and if $k = j$, we obtain own elasticity, otherwise we have cross elasticity.

$P_i^{MKT_k}(j \mid inc)$ =Brand choice probability for brand *j*.

$P_i^{*MKT_k}(j \mid inc)$ =Brand choice probability for a 1% increase in a marketing variable for brand *k*.

Table 8 provides calculated own and cross elasticities and the second to fifth columns represent the brands whose price, discount, and the number of product facings in the displays were increased by 1%. First, we find that a 1% change of one brand's marketing activity influences consumers' purchase incidence probability but the influence is different across activities. Among different display locations, increasing the number of product facings in end cap displays enhances purchase incidence the most (front end cap: from 0.019 to 0.348 across brands, 0.207 on average; rear end cap: from 0.056 to 0.371 across brands, 0.206 on average), followed by shelf (from 0.041 to 0.296, 0.165 on average), while increasing product facings in store rear displays has the smallest impact (from 0.005 to 0.016, 0.010 on average). Offering a higher discount also elevates purchase incidence (from 0.050 to 0.273, 0.167 on average). Overall, the result is consistent with the size of posterior estimates in Table 5 in that end caps and shelf displays and discount show the largest effect sizes. In addition, purchase incidence elasticities in Table 8 is discrepant across brands. Specifically, Coke's change of marketing activities influences purchase incidence the most, whereas the other two manufacturer brands, Pepsi and Dr. Pepper, show lower effects than the private brand for some display locations like endcaps and shelf, indicating that smaller brands can increase the purchase incidence when displayed at highly accessible locations.

Next, Table 8 provide brand choice elasticities upon changing marketing activities. Across all brands and marketing activities, own elasticities that are italicized are much larger than cross elasticities, showing that each brand is the main recipient of its own enhanced marketing effect. The magnitude of own brand elasticities is consistent with posterior estimates in Table 7, especially displays, in that front and rear end cap and shelf displays have stronger own elasticities than store front, store rear, and secondary displays. When looking across brands, brands with larger market shares get higher positive elasticities and lower negative elasticities, whereas the pattern is opposite (i.e., lower positive and higher negative elasticities) for the private brand. For instance, Coke has the highest brand choice elasticity due to shelf displays (1.306) and price (-2.781), while the private brand has the lowest, 0.810 for shelf and -3.515 for price, respectively. Cross elasticities also demonstrate discrepancies across brands. The private brand is the most vulnerable for manufacturer brands' increased marketing activities. For example, when Coke increases the number of product facings in front end cap display (shelf display) by 1%, the effect on private brand's choice probability is -0.432 (-0.385), whereas that on Pepsi and Dr. Pepper is -0.206 (-0.210) and -0.151 (-0.159), respectively. Conversely, Coke is affected mostly by an increase of Pepsi's display (from -0.189 to 0.004, -0.111 on average) and has the least impact based on the private brand (from -0.102 to 0.002, -0.053 on average) displays.

In addition, the magnitude of cross brand elasticities is different across display locations. Increasing the number of product facings in one brand's shelf display results in the largest negative cross brand elasticities (-0.207 on average). The location of shelf displays is in the main aisle of a product category where all brands exist, so increasing one brand's number of product facings in displays is likely to harm other brands by depriving shelf space and catching shoppers' attention. On the contrary, store rear is where cross brand elasticities seem the least effective (0 on average). It is likely that the location is mostly used as a hallway for in-store shoppers and occupied with other multiple categories, which may hurt the accessibility and visibility of items displayed. Also, the small size of cross brand elasticities of secondary displays (-0.02 on average) is consistent with the insignificant parameter estimates of secondary displays on brand choice probability in Table 7.

To sum up, the results from the elasticity calculation demonstrate that consumers' sensitivities to in-store marketing activities are different across various types of marketing activities (i.e., displays, discount and price), locations of displays, and market share of brands. Furthermore, retailers should account for differences in cross elasticities when dealing with multi-brand in-store promotions.

-- Insert Table 8 here --

Optimal Allocation of Displays

In addition to describing consumers' sensitivities through elasticities, we conduct simulations to optimally allocate the displays across brands from both the retailer's and category captain's perspectives for demonstrating enhanced revenues. The detailed optimization procedure is discussed in Web Appendix D.

Retailer's revenue maximization

Tables 9 shows the results of our optimization approach for randomly chosen four weeks. Consistent with the previous sections, the numbers in the table refer to the number of product facings available at each display location. We find that for each display at the brand level, the optimized numbers are quite different from the observed numbers. The proposed solution yields higher retailer revenue than observed revenue for all weeks. For each week, revenue increases between 9.61% to 13.37%, resulting in an increase of 11.15% on average.

Results demonstrate that if the goal is to maximize the retailer's revenue, then one possible option is to decrease the number of product facings in specific displays for manufacturer brands and promote displays of its own brand. In particular, the sum of product facings in proposed displays of the private brand across the four weeks is 4,642 while the sum of those in the current observed displays is 748. Our proposed approach goes further in describing the brands that should reduce their number of displays. We find that the largest part of the private brand's increase comes from a decrease in large manufacturer brands' displays. Coke has the largest amount of decrease among the three manufacturer's brands for the two weeks -2,437 (the total number of product facings in proposed displays: 2,521; the total number in observed displays: 4,958), following by Pepsi: -935 (the total number in proposed displays: 1,684; the total number in observed displays: 2,619). Dr. Pepper shows the smallest difference: -522 (the total number in proposed displays: 1,350; the total number in observed displays: 1,872). Hence, the strategy of the largest market share brand having the largest number of displays turns out to be detrimental in terms of the revenue to the retailer.

Furthermore, we find that contrary to the observed numbers it is a good strategy to distribute the displays across all locations of the store. Specifically, based on observed data, the only brand that is displayed at store front was Coke in week 3 and Pepsi in week 23 and 30, respectively. The private brand is only displayed in front cap in week 3, 23, and 30 and not displayed at all in rear cap and secondary display location across all weeks. However, our proposed solution suggests all brands having a certain number of displays at every location to enhance shopper exposure. In addition, the number of proposed displays of the private brand is comparable with that of Coke at less exclusive and more visible locations, such as storefront and end caps in most weeks. However, when the location is exclusive for the category (i.e., shelf), the proposed solution shows a much higher number for the private brand than other manufacturer brands. Such a difference confirms the discrepant effect of display locations on purchase incidence and brand choice, in that retailers can attract consumers' purchase of the category through manufacturer brands displayed at more visible and frequently visited locations and induce consumers to purchase the private brand with increased displays at shelf. To sum up, retailers can have higher revenue by increasing the displays of the private brand, allowing all brands to be displayed at every location instead of letting one brand dominate a specific type of display, and selectively using locations for boosting purchase incidence and brand choice, if they have full authority of displaying merchandise. However, we caution that our optimization simulation does not incorporate slotting fees from manufacturer brands due to data unavailability, which could be an interesting future research direction.

-- Insert Table 9 here--

Category captain's revenue maximization

Some retailers let a large supplier or manufacturer manage the product category to overcome their lack of resources to intensively manage all product categories (Gooner, Morgan, and Perrault Jr 2011) and also allocate different displays to different brands as part of the category management task. To investigate the allocation of displays under this "category captain" concept, we change the objective function for our optimization routine. We use the brand with the largest market share, Coke, as the category captain and maximize its revenue.

Table 10 summarizes the result of our optimization approach to maximizing Coke's revenue for four weeks. The revenue from the proposed solution is higher than the observed revenue across all weeks, in that it increases by 7.34% to 13.41% (10.29% on average). Furthermore, we find that the retailer's revenue also increases by 4.08% to 7.53% (6.03% on average) and this indicates that letting Coke manage the category contributes to improvement in retailer revenue as well. The results for the reallocation of the displays demonstrate that one possible strategy to maximize Coke's revenue is not simply focusing on increasing the total number of product facings in its own displays. The optimal number of product facings in Coke's displays is 5,347 that is 7.8% increase from the observed number (4,958). This incremental number is much smaller than the solution for maximizing retailer revenue, as discussed in the previous section, proposing that the retailer should increase the display of its own brand by about six times (from 748 to 4,642). In terms of location, the optimal displays for Coke should be allocated across all locations. This is different from current observed displays for Coke as it is not displayed in store front in week 18, front cap in all weeks, and rear cap in week 18. The display re-allocation strategy based on maximizing category captain's revenue also differs from the strategy of maximizing retailer's revenue because the proposed solution does not display other brands at some alternate locations (e.g., no displays for the private brand in store front in week 23 and no displays for Pepsi in rear cap in week 30). Therefore, we find that for a large brand like Coke, increasing the total number of product facings in its own displays is less important. Instead, having Coke displayed in all locations can be a more important criterion for maximizing its revenue.

Another possible option for Coke to maximize revenue is to reduce displays for national brands and increase displays for the private brand. Based on our optimization, the private brand is the one that demonstrates an increase in the number of product facings in displays from 748 (observed) to 2,429 (proposed) whereas the sum of product facings in displays of all national brands decreases from 9,449 (observed) to 7,768 (proposed). This pattern is similar to that of the solution for maximizing retailer revenue in Table 8, but the amount of change is much smaller than in Table 9, in that the sum of optimal displays of the private brand is 4,642 in Table 9 and 2,429 in Table 10. Promoting displays of the private brand seems to contribute to the improvement of Coke's revenue up to a certain point beyond which it aids the retailer more than Coke. Based on our optimization approach, we find implications for both retailers and the largest brand in the soft drink category. Even though our optimal solution is a conservative estimate as it is based on a limited local optimum due to lack of information on managers' judgments, we still find that the proposed increase in revenue is not negligible, as the proposed solution does not increase the total number of product facings in displays across brands.

-- Insert Table 10 here--

Discussion, Conclusion and Future Research

In this research, we investigate a very fundamental issue pertinent to retailers, i.e., capturing the impact of various types of in-store displays. Specifically, we extend past research by investigating the impact of six different types of in-store displays at different locations within the store (e.g., store front, in-aisle, secondary locations). We demonstrate that by accounting for the differential impact across different brands and optimizing various displays across multiple locations and brands in a store, retailers or category captains can indeed increase their revenues.

We make important contributions on multiple fronts. Theoretically, we use the SOR theory with an emphasis on the cognitive processing (attention and information processing) as an overarching framework to discuss the role of different types of in-store displays. We distinguish the differential impact of displays that are closer (front end cap, rear end cap, and shelf) and farther away (storefront, store rear, and secondary displays) from the focal category on purchase incidence and brand choice. We also delve deeper into specific displays across our broader classification, and demonstrate that front end cap displays are the most effective in driving category purchase incidence, while shelf displays are the most effective in driving brand choice. Similarly, for displays farther from the focal category, we find that storefront displays are the most effective in driving category purchase incidence. These insights about the impact of different types of displays would be invaluable for retailers.

Substantively, we capture the differential impacts of in-store displays. In particular, all the displays have a highly significant impact as they are different in terms of elevating consumers' purchase intention across locations. Not only the main effects but also interactions between displays and between displays and price and discounts are different. Furthermore, we find some displays to be detrimental to brand choice as they are successful in capturing shopper attention towards the product category but lead to the choice of non-displayed brands. In addition, we demonstrate a display allocation optimization that results in a revenue increase of up to 13.37% to the retailer while the proposed approach does not require any increase in the total number of product facings in displays or additional space. The increase is confirmed across multiple weeks and multiple entities in charge of managing displays.

Retail managers face a number of great challenges including the difficulty of attracting consumers' attention and interests to the displayed products and examining the effectiveness of different types of displays to improve shopper experience and maximize overall revenues or profits. Our results aim to provide managers with success metrics on historically displayed discounts that can aid their future decision making. Currently, our proposed methodology and findings assume that customers always see the displays. However, a possible avenue for future research would be to extend our approach to a new type of dataset that track consumers and measures the actual amount/duration of attention on various displays. Another interesting future research direction is to examine the different theoretical characteristics (e.g., visibility, exclusivity, informativeness) of various displays and the role of cognitive states of customers in understanding the impact of displays on purchases by using lab or field experiments.

In addition, our proposed optimization technique adheres to a more conservative approach and we believe that alternative approaches that relax some of our assumptions could lead to a further increase in retailer revenues. Our investigation of displays is specific to one large retailer and one category within the retailer. Future research can look into the cross-category impact of displays and impacts across different stores and layouts, as well as the joint negotiation process between retailers and manufacturers. In addition, current research does not include information about retailer's slotting fees for different brands. Future research should extend our optimization findings by incorporating slotting allowances which we currently assume to be the same across different brands. Moreover, the optimization results of store front and store rear could have both category and brand oriented effects[6]. Finally, information about competing stores would be an interesting addition for future research to pursue as this could broaden the scope of investigating the role of in-store displays further.

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TABLE 1. Summary of Previous Literature

Study	***Main Theory***	***Multiple in-store display locations (numbers)***	***Interaction between displays***	***Interaction between displays and other promotional variables***	***Category incidence***	***Brand choice***	***Alternative way of displaying products***	***Main Findings***
Gupta (1988)	Brand choice, inter-purchase time, and purchase quantity	-	-	-	√	√	-	The decomposed sales bump during an in-store price promotion shows that the increased sales consists of 84% of consumers' brand switching, 14% of purchase acceleration, and 2% of stockpiling.
Bemmaor and Mouchoux (1991)	Empirical investigation using Factorial experiment	-	-	√	-	√	-	The effects of price promotions are not constant among different sized national brands, and positively interact with in-store advertising including displays where the size is weaker for leading brands.
Drèze, Hoch, and Purk (1995)	Information processing	-	-	-	√	√	√	Between two shelf management techniques, "space to movement" results in changes in both sales and profits, while "product reorganization" leads to changes in sales. Most products are found to be over-allocated in shelves.
Allenby and Ginter (1995)	Consideration sets	-	-	-	-	√	-	Consideration sets are more than combinations of preferred brands and displays and features decrease the price sensitivity. Displays and features affect competition patterns in a consideration set.
Anderson and Simester (1998)	Demand uncertainty	-	-	√	√	-	-	Consumers' demand may be affected by in-store sale signs because the sale signs signal credibility on products being discounted. Sale signs justify price premium charged by stores.
Anderson and Simester (2001)	Credibility; Attention; Substitution	-	-	-	√	√	-	The effect of sale signs is weak when applied to more items, when some but not all products have sale signs the category sales are maximized, and the perception on the lower price in the future decreases with a sale sign.
Inman, Winer, and Ferraro (2009)	Affect and appraisal; Unplanned purchase; Self-control	-	-	-	√	√	-	Consumers' in-store decision making depend on category characteristics (e.g., displays) and consumer characteristics. Contextual factors boost the probability of making unplanned purchases from 46% to 93%.
Chandon, Hutchinson, Bradlow, and Young (2009)	Information processing	-	-	-	-	√	-	Number of product facings affects consumers' attention which further drives brand evaluation, and the effect on attention and evaluation is different across shelf positions. Some out-of-store factors and willingness to trade off brand and price moderate the effect of the number of product facings.
Bell, Corsten, and Knox (2011)	Construal level theory; Unplanned purchase	-	-	-	√	-	-	When the shopping goal set prior to a shopping trip is abstract, unplanned buying increases monotonistically. Consumers' goals regarding a store affect unplanned buying.
Breugelmans and Campo (2011)	Attention at the point of purchase; Hedonic vs. utilitarian shopping attitude	√ (3)	-	√	√	√	-	The effect of in-store displays in online stores is found. Among the three displays, first screen displays double the brand market share compared to aisle displays, while shelf tag displays have no significant effects.
Lee, Kim, and Allenby (2013)	Multi-category demand	-	-	-	√	√	-	The results show that asymmetric spillover effects of promotions happen due to the asymmetric interdependency in utility, and ignoring such asymmetric effects lead to biased estimates.
This research	SOR theory; Information processing	√ (6)	√	√	√	√	√	Various display locations have differential impacts on consumers' purchase incidence and brand choice. The synergistic effects between displays and other marketing variables like price and discounts are also demonstrated. An optimization strategy for allocating products across display locations that increases both retailer and category captain's revenues is proposed.

TABLE 2. Characteristics of Different Displays

Characteristics	*Store Front Display*	*Store Rear Display*	*Secondary Display*	*Front Endcap Display*	*Rear Endcap Display*	*Shelf Display*
Physical Characteristics						
Location	Store front	Store rear	Other open area	Front end of the category aisle	Rear end of the category aisle	In the category aisle
Proximity to focal category	Farther	Farther	Farther	Closer	Closer	Closest
Size of displayed area	Large	Large	Large/Medium	Medium	Medium	Large
Focus on a Brand/Category	Category or brand	Category or brand	Category or brand	Brand	Brand	Brand
Content Characteristics						
Shape of fixtures	Bins, cases, windows	Bins, cases, shelfs, hooks, banner	Bins, cases, shelfs, hooks, gondola, banner	Medium shelf	Small shelf	Large shelves or gondolas
Color	Matching product category or brand	Varied	Varied	Varied	Varied	Matching brand color
Material	Cardboard, wood, metal, plastic	Cardboard, wood, metal, plastic	Cardboard, wood, metal, plastic	Wood, metal	Wood, metal	Wood, metal, cardboard, plastic
Information	Detailed	Detailed	Detailed	Medium	Medium	Medium
Price Promotion	Category or brand promotion	Category or brand promotion	Category or brand promotion	Brand promotion	Brand promotion	Brand promotion
Theoretical Characteristics						
Purpose	Category or brand purchase	Category or brand purchase	Category or brand purchase	Brand purchase	Brand purchase	Brand purchase
Accessibility	Very high	Medium	High	High	Medium	Low
Visibility	Very high	Medium	High	High	Medium	Low
Exclusivity	Low	Low	Medium	High	High	Very high
Informativeness	High	High	High	Medium	Medium	Medium
Price Promotion Orientation	Category or brand	Category or brand	Category or brand	Brand	Brand	Brand

TABLE 3. Variable Descriptions

Model	*Variable*	*Description*
Purchase incidence	$STFR_t$	The number of product facings in store front display at time *t*.
	$STRR_t$	The number of product facings in store rear display at time *t*.
	$SCDR_t$	The number of product facings in secondary display at time *t*.
	$FCAP_t$	The number of product facings in front endcap display at time *t*.
	$RCAP_t$	The number of product facings in rear endcap display at time *t*.
	$SHLF_t$	The number of product facings in shelf display at time *t*.
	$DISC_t$	The average price discount per ounce of the category at time *t*.
	$PRICE_{ct}$	The average sticker price per ounce of the category at time *t*.
	Cat_REC_i	The cumulative average difference of weeks between the current and last purchase of the category of household *i*.
	Cat_FREQ_i	The cumulative average purchase frequency of the category of household *i* from past shopping trips.
	Cat_MNTR_i	The cumulative average amount of dollar spent for the category from past shopping trips of household *i*.
	$NFEAT_{t-1}$	The number of different types of feature of the category at time *t –1*.
	$STFROT_t$	The no. of product facings in store front display of other categories at time *t*.
	$STRROT_t$	The no. of product facings in store rear display of other categories at time *t*.
	$SCDROT_t$	The no. of product facings in secondary display of other categories at time *t*.
	LP_{it}	1 if the category is purchased in the last purchase of household *i*.
	LQ_{it}	The mean-centered quantity from past shopping trips of household *i*.
	EVENT	1 if the transaction happens in the week of the Super Bowl, NCAA tournament games, and Independence Day.
	FWEEK	1 if the transaction occurs in the first week of February and June, to control the missing transactions of January and May 2013.
Brand choice	$STFR_{jt}$	The number of product facings in store front display of brand *j* at time *t*.
	$STRR_{jt}$	The number of product facings in store rear display of brand *j* at time *t*.
	$SCDR_{jt}$	The number of product facings in secondary display of brand *j* at time *t*.
	$FCAP_{jt}$	The number of product facings in front endcap display of brand *j* at time *t*.
	$RCAP_{jt}$	The number of product facings in rear endcap display of brand *j* at time *t*.
	$SHLF_{jt}$	The number of product facings in shelf display of brand *j* at time *t*.
	$DISC_{jt}$	The average price discount per ounce of brand *j* at time *t*.
	$PRICE_{jt}$	The average sticker price per ounce of brand *j* at time *t*.
	$COMPS_{jt}$	The number of product facings of competing brands that are displayed at the same location for brand *j* at time *t*
	$COMPD_{jt}$	The number of product facings of competing brands that are displayed at different locations for brand *j* at time *t*
	LB_{ijt}	1 if the brand is purchased in the last purchase of household *i*.

TABLE 4. Descriptive Statistics of Variables

Model	*Variable*	*Mean/ Percentage*	*SD*	*Min*	*Max*
Purchase incidence	STFR$_{t}$	20.489	44.432	0	161
	STRR$_{t}$	3.17	21.291	0	146
	SCDR$_{t}$	1189.809	906.06	0	4349
	FCAP$_{t}$	62.255	85.855	0	242
	RCAP$_{t}$	199.489	202.882	5	739
	SHLF$_{t}$	1036.745	737.069	21	2341
	DISC$_{t}$	-0.006	0.003	-0.014	0
	PRICE$_{ct}$	0.034	0.009	0.029	0.035
	Cat_REC$_{i}$	2.315	1.402	0	8.5
	Cat_FREQ$_{i}$	8.36	5.661	0	22.5
	Cat_MNTR$_{i}$	0.032	0.028	0	88.107
	NFEAT$_{t-1}$	2632.957	1418.11	7	6711
	STFROT$_{t}$	33.553	117.911	0	644
	STRROT$_{t}$	416.979	336.054	0	1131
	SCDROT$_{t}$	53.702	114.97	0	491
	LP$_{it}$	21.40%	-	0	1
	LQ$_{it}$	0.01	0.153	-3.637	2.488
	EVENT	22.50%	-	0	1
	FWEEK	4.00%	-	0	1
Brand choice	STFR$_{Coke,t}$	10.043	36.202	0	161
	STRR$_{Coke,t}$	3.170	21.291	0	146
	SCDR$_{Coke,t}$	503.979	502.854	0	2267
	FCAP$_{Coke,t}$	0	0	0	0
	RCAP$_{Coke,t}$	101.404	159.704	0	718
	SHLF$_{Coke,t}$	602.745	535.975	0	1811
	DISC$_{Coke,t}$	-0.008	0.003	-0.014	-0.003
	PRICE$_{Coke,t}$	0.038	0.002	0.031	0.041
	COMPS$_{Coke,t}$	2.340	0.600	0	3
	COMPD$_{Coke,t}$	0.872	1.013	0	3
	LB$_{Coke,t}$	23.50%	-	0	1
	STFR$_{Pepsi,t}$	9.596	29.418	0	111
	STRR$_{Pepsi,t}$	0	0	0	0
Brand Choice	SCDR$_{Pepsi,t}$	436.340	318.540	0	1420
	FCAP$_{Pepsi,t}$	2.851	15.619	0	104
	RCAP$_{Pepsi,t}$	61.021	68.185	0	320
	SHLF$_{Pepsi,t}$	191.638	191.212	0	648
	DISC$_{Pepsi,t}$	-0.008	0.002	-0.013	-0.005
	PRICE$_{Pepsi,t}$	0.039	0.002	0.034	0.044
	COMPS$_{Pepsi,t}$	2.447	0.619	0	3
	COMPD$_{Pepsi,t}$	0.638	0.792	0	3
	STRR$_{Pepsi,t}$	0	0	0	0
	LB$_{Pepsi,t}$	22.56%	-	0	1
	STFR$_{Dr.Pepper,t}$	0.851	5.405	0	37
	STRR$_{Dr.Pepper,t}$	0	0	0	0
	SCDR$_{Dr.Pepper,t}$	204.894	154.221	0	662
	FCAP$_{Dr.Pepper,t}$	0	0	0	0
	RCAP$_{Dr.Pepper,t}$	37.064	92.038	0	485
	SHLF$_{Dr.Pepper,t}$	217.426	162.595	3	586
	DISC$_{Dr.Pepper,t}$	-0.008	0.002	-0.013	-0.005
	PRICE$_{Dr.Pepper,t}$	0.036	0.002	0.031	0.041
	COMPS$_{Dr.Pepper,t}$	2.340	0.600	0	3
	COMPD$_{Dr.Pepper,t}$	1.255	1.031	0	3
	LB$_{Dr.Pepper,t}$	8.98%	-	0	1
	STFR$_{PrivateBrand,t}$	0	0	0	0
	STRR$_{PrivateBrand,t}$	0	0	0	0
	SCDR$_{PrivateBrand,t}$	44.596	76.162	0	222
	FCAP$_{PrivateBrand,t}$	59.404	86.229	0	242
	RCAP$_{PrivateBrand,t}$	0	0	0	0
	SHLF$_{PrivateBrand,t}$	24.936	64.975	0	343
	DISC$_{PrivateBrand,t}$	-0.001	0.001	-0.003	0
	PRICE$_{PrivateBrand,t}$	0.016	0	0.015	0.017
	COMPS$_{PrivateBrand,t}$	1.234	1.339	0	3
	COMPD$_{PrivateBrand,t}$	2.851	0.510	0	3
	LB$_{PrivateBrand,t}$	12.65%	-	0	1

TABLE 5. Correlations between Product Purchases and Displays (Soft drink)

	Overall	*Quarter 1*	*Quarter 2*	*Quarter 3*	*Quarter 4*
STFR	0.548	-0.370	0.177	0.518	-0.904
STRR	-0.065	NA	-0.067	NA	NA
SCDR	0.166	-0.086	-0.076	0.327	0.856
FCAP	0.714	NA	0.773	0.626	-0.432
RCAP	0.100	0.520	0.023	0.378	0.744
SHLF	0.231	0.170	0.595	0.347	0.920

TABLE 6. Posterior Estimates for the Proposed Model (Purchase Incidence)

Parameters		**Mean**				**SD**			
		Intercept	*Gender*	*Income*	*HHsize*	*Intercept*	*Gender*	*Income*	*HHsize*
Intercept		-0.023	-0.073	0.026	0.023	0.069	0.056	0.064	0.093
Marketing activities	STFR$_t$	**0.179**	**-0.125**	**-0.275**	**0.579**	0.077	0.072	0.108	0.104
	STRR$_t$	0.098	-0.064	**-0.377**	**0.343**	0.093	0.082	0.075	0.169
	SCDR$_t$	0.008	**0.283**	**-0.717**	**0.619**	0.095	0.08	0.056	0.075
	FCAP$_t$	**0.434**	0.128	-0.017	**-0.244**	0.09	0.097	0.073	0.08
	RCAP$_t$	**0.353**	0.083	-0.155	**0.141**	0.081	0.052	0.126	0.081
	SHLF$_t$	**0.346**	-0.081	**0.262**	-0.167	0.197	0.053	0.097	0.113
	DISC$_t$	**0.59**	**-0.184**	**-0.189**	**-0.304**	0.089	0.041	0.074	0.145
	PRICE$_{ct}$	**-0.293**	**0.48**	-0.025	**0.209**	0.096	0.067	0.07	0.073
	STFR$_t$ × STRR$_t$	0.08	**0.407**	**0.199**	**-0.92**	0.103	0.085	0.054	0.086
	STFR$_t$ × SCDR$_t$	**0.129**	**-0.295**	-0.043	**-0.259**	0.062	0.055	0.049	0.117
	STFR$_t$ × FCAP$_t$	**0.918**	**-0.318**	**-0.256**	**-0.173**	0.158	0.074	0.066	0.067
	STFR$_t$ × RCAP$_t$	**0.585**	0.065	0.012	**-0.146**	0.083	0.045	0.063	0.063
	STFR$_t$ × SHLF$_t$	**0.784**	0.08	**0.327**	0.089	0.119	0.066	0.086	0.148
	STRR$_t$ × SCDR$_t$	0.023	-0.13	-0.07	0.032	0.124	0.082	0.095	0.074
	STRR$_t$ × FCAP$_t$	**0.42**	0.063	**-0.346**	**-0.168**	0.075	0.047	0.076	0.105
	STRR$_t$ × RCAP$_t$	**0.24**	**0.138**	**-0.224**	-0.007	0.102	0.061	0.094	0.062
	STRR$_t$ × SHLF$_t$	**0.351**	0.06	**-0.234**	0.013	0.109	0.06	0.06	0.088
	SCDR$_t$ × FCAP$_t$	**0.627**	**-0.288**	0.061	**-0.21**	0.092	0.085	0.102	0.087
	SCDR$_t$ × RCAP$_t$	**0.512**	**0.076**	**0.307**	**0.319**	0.075	0.042	0.123	0.091
	SCDR$_t$ × SHLF$_t$	**0.492**	**0.1**	**-0.328**	**0.442**	0.069	0.045	0.063	0.079
	FCAP$_t$ × RCAP$_t$	**1.179**	**-0.411**	**-0.377**	**-0.484**	0.164	0.06	0.074	0.072
	FCAP$_t$ × SHLF$_t$	**1.841**	**0.21**	**0.12**	0.028	0.128	0.07	0.062	0.113
	RCAP$_t$ × SHLF$_t$	**1.574**	**-0.27**	**-0.248**	**-0.139**	0.112	0.079	0.069	0.078

	$DISC_t \times STFR_t$	**0.271**	0.093	**-0.309**	**0.168**	0.085	0.057	0.064	0.082
	$DISC_t \times STRR_t$	-0.044	**-0.394**	**0.205**	0.124	0.09	0.044	0.064	0.111
	$DISC_t \times SCDR_t$	**0.154**	-0.024	**0.157**	-0.105	0.064	0.056	0.067	0.068
	$DISC_t \times FCAP_t$	**0.65**	**0.362**	**-0.148**	0.079	0.085	0.073	0.068	0.125
	$DISC_t \times RCAP_t$	**0.547**	**-0.234**	0.102	**0.335**	0.068	0.059	0.108	0.134
	$DISC_t \times SHLF_t$	**0.503**	**0.113**	0.041	0.01	0.069	0.057	0.055	0.081
	$PRICE_t \times STFR_t$	**0.123**	**-0.184**	**-0.281**	**0.328**	0.07	0.045	0.138	0.092
	$PRICE_t \times STRR_t$	-0.065	**-0.285**	**0.106**	**-0.329**	0.062	0.046	0.055	0.088
	$PRICE_t \times SCDR_t$	-0.036	-0.088	**0.541**	**-0.217**	0.081	0.092	0.054	0.135
	$PRICE_t \times FCAP_t$	**0.527**	**-0.111**	**-0.239**	**-0.213**	0.119	0.047	0.091	0.061
	$PRICE_t \times RCAP_t$	**0.516**	0.058	**-0.283**	0.048	0.109	0.051	0.057	0.061
	$PRICE_t \times SHLF_t$	**0.414**	**-0.081**	0.138	**0.297**	0.13	0.046	0.083	0.089
Customer's past purchase behavior	Cat_REC_i	**-0.379**	**0.079**	0.076	**-0.337**	0.131	0.045	0.068	0.088
	Cat_FREQ_i	**-0.46**	**0.184**	**-0.488**	-0.089	0.174	0.062	0.162	0.101
	Cat_MNTR_i	**-0.225**	**0.183**	-0.094	0.103	0.087	0.042	0.103	0.094
	$NFEAT_{t-1}$	0.003	**0.314**	0.022	**0.255**	0.072	0.045	0.078	0.058
	LP_{it}	**0.295**	**-0.279**	-0.079	**-0.357**	0.119	0.07	0.083	0.071
	LQ_{it}	**-0.281**	**-0.299**	**0.41**	0.16	0.112	0.047	0.104	0.153
Competitions and Control variables	$STFROT_t$	**-0.313**	-0.085	**-0.188**	-0.094	0.105	0.079	0.076	0.111
	$STRROT_t$	**-0.412**	**0.121**	0.014	0.011	0.097	0.047	0.145	0.08
	$SCDROT_t$	0.171	**-0.247**	**-0.134**	0.046	0.143	0.062	0.058	0.069
	EVENT	**0.233**	**-0.111**	**-0.104**	0.076	0.124	0.067	0.053	0.059
	FWEEK	-0.064	**0.147**	0.223	**0.16**	0.104	0.049	0.177	0.091
Inclusive value		**0.44**	-0.065	**0.171**	**-0.247**	0.118	0.048	0.094	0.064

TABLE 7. Posterior Estimates for the Proposed Model (Brand Choice)

Parameters		Mean				SD			
		Intercept	*Gender*	*Income*	*HHsize*	*Intercept*	*Gender*	*Income*	*HHsize*
Intercept	Coke	**0.272**	**0.154**	-0.043	-0.048	0.086	0.079	0.079	0.119
	Pepsi	**0.222**	**-0.46**	0.02	**-0.338**	0.106	0.077	0.08	0.102
	Dr.Pepper	**0.117**	-0.03	0.046	**0.157**	0.066	0.068	0.059	0.062
	Private Brand	**-1.201**	**-0.483**	**-0.419**	**-0.634**	0.109	0.048	0.083	0.106
Marketing activities	$STFR_{jt}$	**0.434**	**-0.39**	**0.111**	**-0.499**	0.094	0.049	0.062	0.073
	$STRR_{jt}$	**-0.195**	**-0.215**	**0.411**	**0.59**	0.093	0.042	0.056	0.143
	$SCDR_{jt}$	-0.134	**0.214**	**0.357**	**-0.195**	0.152	0.06	0.073	0.08
	$FCAP_{jt}$	**0.811**	-0.094	**0.247**	-0.098	0.078	0.081	0.063	0.094
	$RCAP_{jt}$	**0.775**	**-0.202**	**-0.503**	0.048	0.174	0.043	0.058	0.078

	$SHLF_{jt}$	**1.195**	**-0.21**	**0.137**	**0.43**	0.1	0.068	0.078	0.104
	$DISC_{jt}$	**0.286**	0.001	**-0.516**	-0.037	0.085	0.055	0.068	0.088
	$PRICE_{jt}$	**-0.982**	**0.157**	**0.151**	**-0.211**	0.098	0.08	0.068	0.066
	$STFR_{jt} \times STRR_{jt}$	-0.09	**0.159**	0.076	**0.532**	0.106	0.088	0.067	0.109
	$STFR_{jt} \times SCDR_{jt}$	**-0.233**	0.035	**0.409**	**-0.112**	0.085	0.053	0.068	0.057
	$STFR_{jt} \times FCAP_{jt}$	**0.475**	-0.078	**0.283**	0.223	0.083	0.106	0.074	0.137
	$STFR_{jt} \times RCAP_{jt}$	**0.314**	**-0.122**	**0.219**	0.075	0.077	0.046	0.057	0.066
	$STFR_{jt} \times SHLF_{jt}$	**0.588**	-0.001	-0.081	0.05	0.072	0.049	0.078	0.111
	$STRR_{jt} \times SCDR_{jt}$	**-0.285**	-0.07	0.064	**-0.731**	0.087	0.044	0.129	0.072
	$STRR_{jt} \times FCAP_{jt}$	**0.199**	**0.233**	-0.092	**0.271**	0.068	0.068	0.07	0.133
	$STRR_{jt} \times RCAP_{jt}$	0.03	0.181	0.077	0.02	0.091	0.113	0.081	0.092
	$STRR_{jt} \times SHLF_{jt}$	**-0.192**	-0.034	**-0.43**	-0.139	0.099	0.075	0.061	0.094
	$SCDR_{jt} \times FCAP_{jt}$	-0.091	**0.187**	0.125	**-0.266**	0.106	0.07	0.065	0.067
	$SCDR_{jt} \times RCAP_{jt}$	-0.015	**-0.162**	**0.148**	-0.068	0.114	0.045	0.069	0.1
	$SCDR_{jt} \times SHLF_{jt}$	**-0.222**	**0.114**	**0.26**	**0.227**	0.091	0.043	0.056	0.073
	$FCAP_{jt} \times RCAP_{jt}$	**0.701**	**0.129**	-0.06	**0.367**	0.108	0.074	0.064	0.072
	$FCAP_{jt} \times SHLF_{jt}$	**1.001**	**-0.121**	**0.218**	**-0.372**	0.067	0.045	0.049	0.123
	$RCAP_{jt} \times SHLF_{jt}$	**0.973**	**-0.618**	**-0.184**	**-0.42**	0.076	0.047	0.063	0.069
	$DISC_{jt} \times STFR_{jt}$	**0.269**	**0.113**	-0.07	0.045	0.1	0.049	0.125	0.073
	$DISC_{jt} \times STRR_{jt}$	-0.106	**-0.24**	**0.433**	**-0.583**	0.093	0.056	0.078	0.07
	$DISC_{jt} \times SCDR_{jt}$	**0.227**	**-0.092**	0.087	0.052	0.083	0.045	0.176	0.069
	$DISC_{jt} \times FCAP_{jt}$	**0.46**	**0.429**	**0.225**	**0.643**	0.129	0.047	0.075	0.061
	$DISC_{jt} \times RCAP_{jt}$	**0.451**	**0.232**	**0.443**	**0.454**	0.081	0.048	0.106	0.055
	$DISC_{jt} \times SHLF_{jt}$	**0.563**	**-0.11**	**-0.318**	**-0.216**	0.094	0.065	0.075	0.111
	$PRICE_{jt} \times STFR_{jt}$	**0.276**	**-0.311**	**-0.16**	0.067	0.103	0.065	0.067	0.061
	$PRICE_{jt} \times STRR_{jt}$	**0.125**	**0.185**	-0.004	**0.295**	0.071	0.083	0.086	0.111
	$PRICE_{jt} \times SCDR_{jt}$	**0.178**	**0.116**	**0.376**	0.027	0.097	0.063	0.053	0.075
	$PRICE_{jt} \times FCAP_{jt}$	**0.962**	**-0.328**	**0.169**	**-0.323**	0.122	0.084	0.058	0.097
	$PRICE_{jt} \times RCAP_{jt}$	**0.703**	**0.17**	-0.013	**0.632**	0.117	0.06	0.15	0.097
	$PRICE_{jt} \times SHLF_{jt}$	**0.974**	0.086	**0.293**	**-0.316**	0.116	0.1	0.062	0.081
Brand loyalty and competitions	LB_{it}	**0.333**	**0.241**	0.09	**-0.323**	0.129	0.045	0.058	0.068
	$COMPS_{jt}$	**-0.363**	**-0.16**	**-0.125**	0.064	0.072	0.095	0.066	0.079
	$COMPD_{jt}$	-0.085	**0.145**	**-0.246**	0.069	0.11	0.067	0.076	0.08
Control variables	EVENT	**0.555**	**0.149**	0.031	0.046	0.122	0.06	0.119	0.069
	FWEEK	**-0.169**	**0.186**	**0.158**	**0.396**	0.084	0.081	0.075	0.12

TABLE 8. Display, Price, and Discount Elasticities

Marketing Activity	Probability		1% increase in: Coke	Pepsi	Dr. Pepper	Private Brand
Store front displays	Purchase incidence		0.134	0.099	0.044	0.094
	Brand choice of	Coke	0.484	-0.143	-0.112	-0.060
		Pepsi	-0.159	0.568	-0.120	-0.077
		Dr.Pepper	-0.134	-0.115	0.463	-0.090
		Private Brand	-0.315	-0.300	-0.337	0.379
Store rear displays	Purchase incidence		0.016	0.012	0.006	0.005
	Brand choice of	Coke	-0.006	0.004	0.000	0.002
		Pepsi	0.001	-0.060	0.001	0.002
		Dr.Pepper	0.000	0.002	-0.091	-0.001
		Private Brand	-0.002	-0.006	-0.007	-0.278
Secondary displays	Purchase incidence		0.020	0.015	0.013	0.010
	Brand choice of	Coke	0.037	-0.014	-0.007	-0.010
		Pepsi	-0.019	0.024	-0.088	-0.015
		Dr.Pepper	-0.012	-0.011	0.011	-0.008
		Private Brand	-0.025	-0.021	-0.013	-0.033
Front endcap displays	Purchase incidence		0.348	0.247	0.019	0.214
	Brand choice of	Coke	1.186	-0.164	-0.131	-0.062
		Pepsi	-0.206	1.009	-0.134	-0.100
		Dr.Pepper	-0.151	-0.143	1.038	-0.105
		Private Brand	-0.432	-0.326	-0.257	0.694
Rear endcap displays	Purchase incidence		0.371	0.181	0.056	0.215
	Brand choice of	Coke	0.828	-0.162	-0.115	-0.083
		Pepsi	-0.172	0.785	-0.108	-0.076
		Dr.Pepper	-0.147	-0.139	0.810	-0.126
		Private Brand	-0.381	-0.338	-0.251	0.621
Shelf displays	Purchase incidence		0.296	0.145	0.041	0.177
	Brand choice of	Coke	1.306	-0.189	-0.131	-0.102
		Pepsi	-0.210	1.146	-0.130	-0.121
		Dr.Pepper	-0.159	-0.161	0.937	-0.172
		Private Brand	-0.385	-0.348	-0.377	0.810
Price	Purchase incidence		-0.289	-0.168	-0.144	-0.039
	Brand choice of	Coke	-2.781	0.457	0.245	1.508
		Pepsi	0.721	-2.760	0.206	1.388
		Dr.Pepper	0.224	0.130	-2.535	1.184
		Private Brand	0.932	1.472	1.145	-3.515
Discount	Purchase incidence		0.273	0.185	0.162	0.050
	Brand choice of	Coke	2.137	-0.287	-0.104	-0.138
		Pepsi	-0.311	2.075	-0.111	-0.127
		Dr.Pepper	-0.124	-0.116	1.717	-0.172
		Private Brand	-0.767	-0.770	-0.549	1.387

TABLE 9. Display Optimization Result (Objective function: Retailer revenue)

Display Location	Brand	Week 3 (N=2804)				Week 18 (N=2748)				Week 23 (N=2186)				Week 30 (N=2459)			
		Observed		Proposed		Observed		Proposed		Observed		Proposed		Observed		Proposed	
Store front	Coke	23	0.82%	7	0.25%	0	0%	0	0%	0	0%	4	0.18%	0	0%	51	2.07%
	Pepsi	0	0%	5	0.18%	0	0%	0	0%	15	0.69%	2	0.09%	104	4.23%	4	0.16%
	Dr. Pepper	0	0%	2	0.07%	0	0%	0	0%	0	0%	3	0.14%	0	0%	3	0.12%
	Private brand	0	0%	9	0.32%	0	0%	0	0%	0	0%	6	0.27%	0	0%	46	1.87%
Store rear	Coke	0	0%	0	0%	146	5.31%	58	2.11%	0	0%	0	0%	0	0%	0	0%
	Pepsi	0	0%	0	0%	0	0%	44	1.60%	0	0%	0	0%	0	0%	0	0%
	Dr. Pepper	0	0%	0	0%	0	0%	30	1.09%	0	0%	0	0%	0	0%	0	0%
	Private brand	0	0%	0	0%	0	0%	14	0.51%	0	0%	0	0%	0	0%	0	0%
Secondary	Coke	2	0.07%	2	0.07%	998	36.32%	574	20.89%	67	3.06%	14	0.64%	756	30.74%	378	15.37%
	Pepsi	5	0.18%	2	0.07%	394	14.34%	340	12.37%	17	0.78%	7	0.32%	637	25.90%	226	9.19%
	Dr. Pepper	0	0%	1	0.04%	232	8.44%	108	3.93%	11	0.50%	3	0.14%	276	11.22%	180	7.32%
	Private brand	0	0%	2	0.07%	0	0%	602	21.91%	0	0%	71	3.25%	0	0%	885	35.99%
Front endcap	Coke	0	0%	60	2.14%	0	0%	35	1.27%	0	0%	28	1.28%	0	0%	60	2.44%
	Pepsi	0	0%	48	1.71%	104	3.78%	15	0.55%	0	0%	13	0.59%	0	0%	32	1.30%
	Dr. Pepper	0	0%	18	0.64%	0	0%	10	0.36%	0	0%	11	0.50%	0	0%	33	1.34%
	Private brand	196	6.99%	70	2.50%	0	0%	44	1.60%	91	4.16%	39	1.78%	233	9.48%	108	4.39%
Rear endcap	Coke	66	2.35%	158	5.63%	0	0%	27	0.98%	34	1.56%	15	0.69%	18	0.73%	6	0.24%
	Pepsi	320	11.41%	105	3.74%	75	2.73%	9	0.33%	51	2.33%	27	1.24%	15	0.61%	12	0.49%
	Dr. Pepper	102	3.64%	45	1.60%	9	0.33%	8	0.29%	10	0.46%	4	0.18%	17	0.69%	10	0.41%
	Private brand	0	0%	180	6.42%	0	0%	40	1.46%	0	0%	49	2.24%	0	0%	22	0.89%
Shelf	Coke	1278	45.58%	458	16.33%	440	16.01%	195	7.10%	971	44.42%	277	12.67%	159	6.47%	114	4.64%
	Pepsi	355	12.66%	355	12.66%	0	0%	128	4.66%	512	23.42%	251	11.48%	15	0.61%	59	2.40%
	Dr. Pepper	457	16.30%	373	13.30%	122	4.44%	75	2.73%	407	18.62%	386	17.66%	229	9.31%	47	1.91%
	Private brand	0	0%	904	32.24%	228	8.30%	392	14.26%	0	0%	976	44.65%	0	0%	183	7.44%
Revenue		2619.13		2880.35		417.05		465.55		6782.88		7689.79		6309.13		6915.51	
% of increase				9.97%				11.63%				13.37%				9.61%	

TABLE 10. Display Optimization Result (Objective function: Coke's revenue)

Display Location	**Brand**	**Week 3 (N=2804)**				**Week 18 (N=2748)**				**Week 23 (N=2186)**				**Week 30 (N=2459)**			
		Observed		Proposed		Observed		Proposed		Observed		Proposed		Observed		Proposed	
Store front	Coke	23	0.82%	8	0.29%	0	0%	0	0%	0	0%	8	0.37%	0	0%	65	2.64%
	Pepsi	0	0%	5	0.18%	0	0%	0	0%	15	0.69%	4	0.18%	104	4.23%	4	0.16%
	Dr. Pepper	0	0%	3	0.11%	0	0%	0	0%	0	0%	3	0.14%	0	0%	3	0.12%
	Private brand	0	0%	7	0.25%	0	0%	0	0%	0	0%	0	0%	0	0%	32	1.30%
Store rear	Coke	0	0%	0	0%	146	5.31%	67	2.44%	0	0%	0	0%	0	0%	0	0%
	Pepsi	0	0%	0	0%	0	0%	33	1.20%	0	0%	0	0%	0	0%	0	0%
	Dr. Pepper	0	0%	0	0%	0	0%	22	0.80%	0	0%	0	0%	0	0%	0	0%
	Private brand	0	0%	0	0%	0	0%	24	0.87%	0	0%	0	0%	0	0%	0	0%
Secondary	Coke	2	0.07%	2	0.07%	998	36.32%	940	34.21%	67	3.06%	54	2.47%	756	30.74%	815	33.14%
	Pepsi	5	0.18%	3	0.11%	394	14.34%	111	4.04%	17	0.78%	29	1.33%	637	25.90%	178	7.24%
	Dr. Pepper	0	0%	1	0.04%	232	8.44%	90	3.28%	11	0.50%	6	0.27%	276	11.22%	100	4.07%
	Private brand	0	0%	1	0.04%	0	0.00%	483	17.58%	0	0%	6	0.27%	0	0%	576	23.42%
Front endcap	Coke	0	0%	87	3.10%	0	0.00%	70	2.55%	0	0%	72	3.29%	0	0%	143	5.82%
	Pepsi	0	0%	35	1.25%	104	3.78%	12	0.44%	0	0%	5	0.23%	0	0%	34	1.38%
	Dr. Pepper	0	0%	20	0.71%	0	0%	6	0.22%	0	0%	3	0.14%	0	0%	15	0.61%
	Private brand	196	6.99%	54	1.93%	0	0%	16	0.58%	91	4.16%	11	0.50%	233	9.48%	41	1.67%
Rear endcap	Coke	66	2.35%	214	7.63%	0	0%	47	1.71%	34	1.56%	62	2.84%	18	0.73%	28	1.14%
	Pepsi	320	11.41%	59	2.10%	75	2.73%	10	0.36%	51	2.33%	8	0.37%	15	0.61%	0	0%
	Dr. Pepper	102	3.64%	41	1.46%	9	0.33%	6	0.22%	10	0.46%	13	0.59%	17	0.69%	4	0.16%
	Private brand	0	0%	174	6.21%	0	0%	21	0.76%	0	0%	12	0.55%	0	0%	18	0.73%
Shelf	Coke	1278	45.58%	1056	37.66%	440	16.01%	328	11.94%	971	44.42%	1144	52.33%	159	6.47%	137	5.57%
	Pepsi	355	12.66%	434	15.48%	0	0%	163	5.93%	512	23.42%	425	19.44%	15	0.61%	30	1.22%
	Dr. Pepper	457	16.30%	141	5.03%	122	4.44%	114	4.15%	407	18.62%	124	5.67%	229	9.31%	124	5.04%
	Private brand	0	0%	459	16.37%	228	8.30%	185	6.73%	0	0%	197	9.01%	0	0%	112	4.55%
Revenue (Coke)		758.68		860.39		196.95		219.56		1669.82		1792.36		2370.64		2582.71	
% of increase				13.41%				11.48%				7.34%				8.95%	
Revenue (Retailer)		2619.13		2816.35		417.05		441.84		6782.88		7059.67		6309.13		6724.15	
% of increase				7.53%				5.94%				4.08%				6.58%	

FIGURE 1: Conceptual Framework

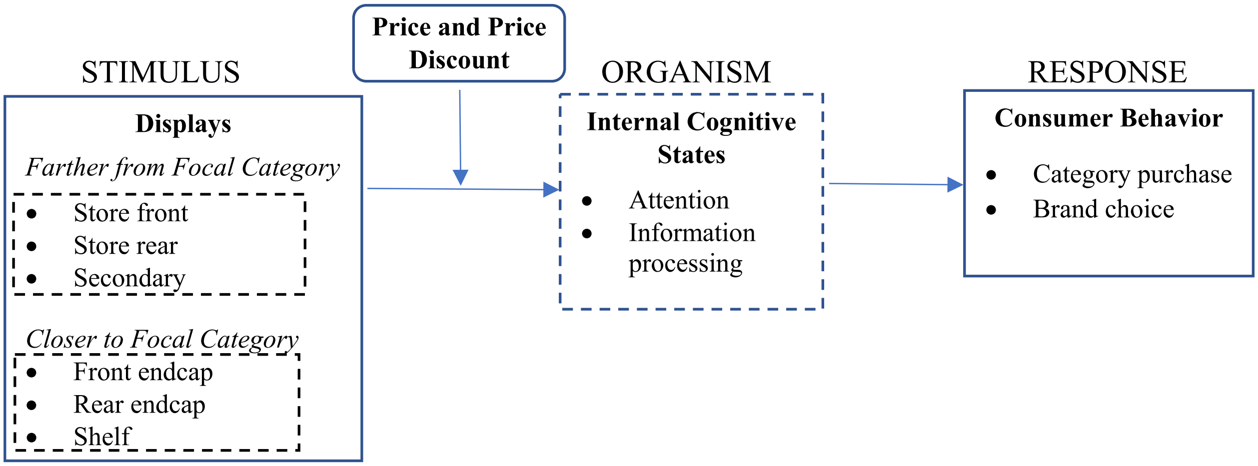
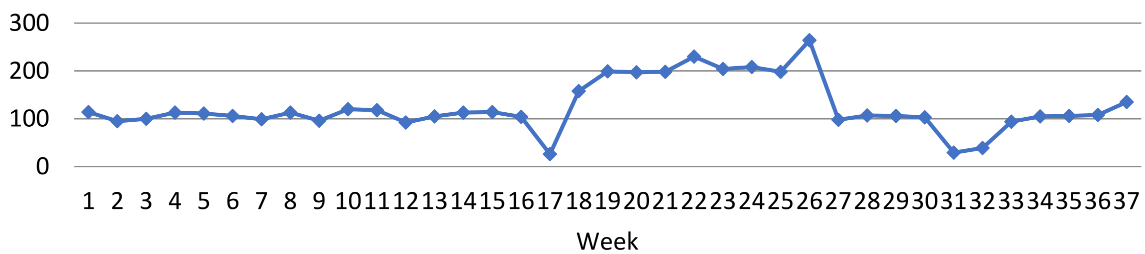
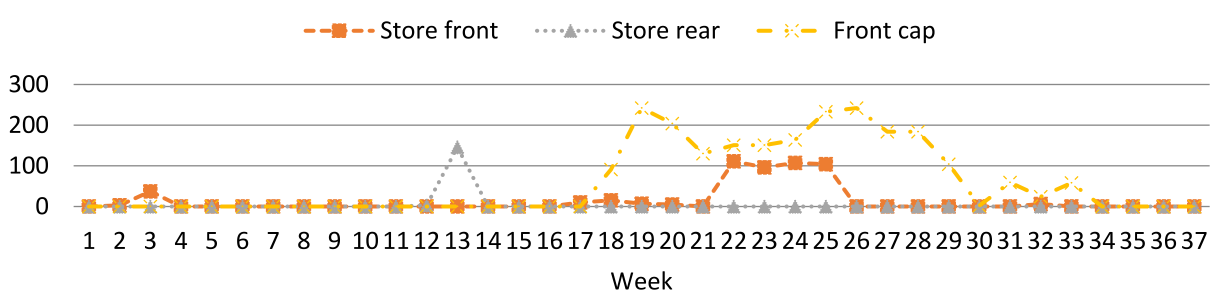


FIGURE 2. The Number of Weekly Purchases and Displays (Soft drink)

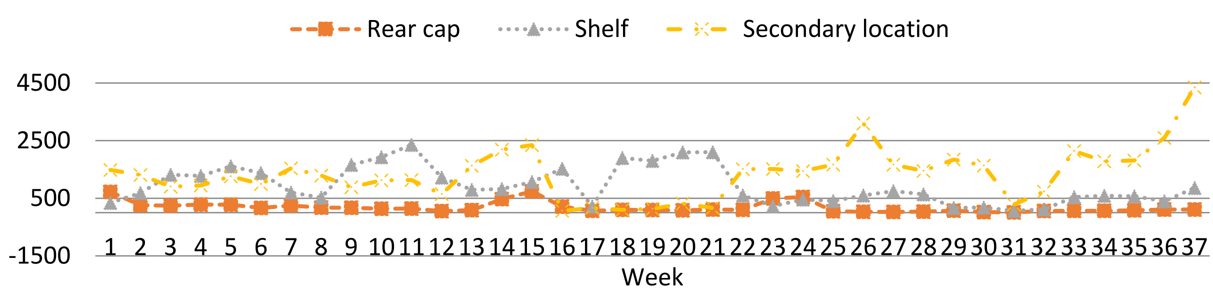
A. The Number of Weekly Purchases



B. The Number of Weekly Displays (1)



C. The Number of Weekly Displays (2)



WEB APPENDIX A: MARKOV CHAIN MONTE CARLO ALGORITHM

Let *i* denote the index of consumer (*i*=1,...,I), let *t* denote the week (*t*=1,...,T), let *j* denote the brand (*j*=1,...,J), and let *d* denote different types of display (*d*=1,...,D).[7]

1. Generate $\{\theta_i\}$

We obtain each respondent's θ_i from equation (4) using the random-walk Metropolis–Hastings algorithm. The algorithm starts with θ_i^d. We then draw the candidate vector, θ_i^n, using the equation

$$\theta_i^n = \theta_i^d + \varepsilon_\theta ,$$

where $\varepsilon_\theta \sim \text{Normal}(0, s_\theta \cdot \Sigma_\zeta)$;

s_θ = .01 is an arbitrary number to control the step size of the random walk chain; and

$\Sigma_\zeta = I_{\#\text{ of parameters}}$, and I indexes identity matrix.

The probability of accepting this candidate vector is given by

$$\text{P(acceptance)} = \min\left\{ \frac{\left[\exp -\frac{1}{2}(\theta_i^n - \Delta Z_i)'\Sigma_\zeta^{-1}(\theta_i^n - \Delta Z_i)\right]\cdot L(\theta_i^n)}{\left[\exp -\frac{1}{2}(\theta_i^d - \Delta Z_i)'\Sigma_\zeta^{-1}(\theta_i^d - \Delta Z_i)\right]\cdot L(\theta_i^d)}, 1 \right\},$$

where $L(\theta_i^n)$ denotes the likelihood function evaluated at θ_i^n. The likelihood function is specified as $L = \prod_i \prod_t \left[P_{it}(inc)^{\tau_{it}} \left[1 - P_{it}(inc)\right]^{1-\tau_{it}} \cdot \prod_j \left[P_{it}(\text{j}\,|\,inc)^{\tau_{ijt}} \left[1 - P_{it}(\text{j}\,|\,inc)\right]^{1-\tau_{ijt}} \right]\right]$, where $\tau_{ijt} = 1$ if brand j was bought by household i at time t, and 0 otherwise, and $\tau_{it} = 1$ if $\sum_j \tau_{ijt} > 0$ and 0 otherwise.

2. Generate Δ

$$\Delta \,|\, Z, \{\theta_i\}, \Sigma_\zeta \sim \text{MVN}(\overline{\overline{\Delta}}, \Sigma_\zeta \otimes (Z'Z + A)^{-1}),$$

where Prior $\Delta \,|\, \Sigma_\zeta \sim \text{Normal}(\overline{\Delta}, \Sigma_\zeta \otimes A^{-1})$

$$\overline{\overline{\Delta}} = (Z'Z + A)^{-1}(Z'Z\Omega + A\overline{\Delta})$$

$$\Omega = (Z'Z)^{-1} Z'\theta$$

$$A = 0.01 \times I$$

3. Generate Σ_ζ

$$\Sigma_\zeta \,|\, Z, \{\theta_i\}, \Delta \sim \text{Inverted Wishart}(\varpi + \text{I}, V + \sum_{i=1}^{\text{I}} (\theta_i - \Delta Z_i)(\theta_i - \Delta Z_i)'),$$

where Prior ϖ = the length of θ_i +3; $V = \varpi \times I$.

4. Generate ξ_t

We obtain ξ_t, the demand shock of the deterministic utility of purchase incidence at each week *t*, using the random-walk Metropolis–Hastings algorithm. The candidate value ξ_t^n is

[7] Here, I=500, T=37, and D=6.

$$\xi_t^n = \xi_t^d + \varepsilon_\xi ,$$

where $\varepsilon_\xi \sim \text{Normal}(0, s_\xi \cdot \Sigma)$,

s_ξ = .005 is an arbitrary number to control the step size of the random walk chain, and

$\Sigma = I_{(2+\mathrm{D})}$.

The acceptance probability of this vector is defined by

$$\text{P(acceptance)} = \min\left\{ \frac{\left[\exp -\frac{1}{2}(\xi_t^n, \kappa_t, \mu_t, \pi_t)'\Sigma^{-1}(\xi_t^n, \kappa_t, \mu_t, \pi_t)\right]\cdot\left(\prod_{i=1}^{\mathrm{I}} L(\xi_t^n)\right)_t}{\left[\exp -\frac{1}{2}(\xi_t^d, \kappa_t, \mu_t, \pi_t)'\Sigma^{-1}(\xi_t^d, \kappa_t, \mu_t, \pi_t)\right]\cdot\left(\prod_{i=1}^{\mathrm{I}} L(\xi_t^d)\right)_t}, 1 \right\},$$

where κ_t is a vector of display-related error terms from equation (6), μ_t is a vector of display-related error terms from equation (7), and π_t is a price-related error term from equation (8). We calculate the time-specific likelihood vector with ξ_t^n and multiply it across individuals. For each time *t*, we use the t^{th} element of the time-specific likelihood vector to calculate the acceptance probability.

5. Generate $\{\eta, \lambda, \nu\}$

Following the approach of Yang et al. (2003) the vector of parameters from instrumental variable specification (equation (6), (7), and (8)) has $(2\times\mathrm{J})(2+\mathrm{D})$ elements and is defined as

$$\{\eta, \lambda, \nu\} \mid \xi, LV, \Sigma \sim \text{MVN}(\psi, \Omega)$$

LV is an array with T matrices and

$$LV_t = \begin{pmatrix}
1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & DISP_{1,1,t-1} & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & DISP_{D,J,t-1} & 0 & \cdots & 0 & 0 & \cdots & 0 \\
0 & \cdots & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & DISC_{1,t-1} & \cdots & 0 & 0 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & DISC_{J,t-1} & 0 & \cdots & 0 \\
0 & \cdots & 0 & 0 & \cdots & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & PRICE_{1,t-1} & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & PRICE_{J,t-1}
\end{pmatrix}$$

The variance-covariance matrix Σ is specified as

$$\Sigma = \begin{pmatrix} \Sigma_\xi & \Sigma_{\xi\kappa\mu\pi} \\ \Sigma_{\xi\kappa\mu\pi} & \Sigma_{\kappa\mu\pi} \end{pmatrix}.$$

$$\psi = \Omega\left(\left(\sum_{t=1}^{\mathrm{T}} LV_t'\Sigma_{\kappa\mu\pi|\xi}(MKT_t - f_t)\right) + V_0\rho_0\right)$$

$$\Omega = \left(V_0^{-1} + \sum_{t=1}^{\mathrm{T}} LV_t'\Sigma_{\kappa\mu\pi|\xi} LV_t\right)^{-1}$$

$$\Sigma_{\kappa\mu\pi|\xi} = \Sigma_{\kappa\mu\pi} - \Sigma_{\xi\kappa\mu\pi}\Sigma_\xi^{-1}\Sigma_{\xi\kappa\mu\pi}'$$

$$MKT_t = \{DISP_{1,1,t}, \cdots, DISP_{D,J,t}, DISC_{1,t}, \cdots, DISC_{J,t}, PRICE_{1,t}, \cdots, PRICE_{J,t}\}'$$

$$f_t = \Sigma_{\xi\kappa\mu\pi}\Sigma_{\xi}^{-1}\xi_t$$
$$\rho_0 = (0,\cdots,0)$$
$$V_0 = 10 \times I_{(2\times \mathrm{J})(2+\mathrm{D})}$$

6. Generate Σ

$$\Sigma \mid LV, \{\eta,\lambda,\nu\}, \xi \sim \text{Inverted Wishart}\left(\sum_{t=1}^{\mathrm{T}}\begin{pmatrix}\xi_t \\ MKT_t - LV_t\{\eta,\lambda,\nu\}\end{pmatrix}'\begin{pmatrix}\xi_t \\ MKT_t - LV_t\{\eta,\lambda,\nu\}\end{pmatrix} + C, \mathrm{T}+c\right)$$

where, Prior c=200; $C = c \times I_{1+\mathrm{J}(3+\mathrm{D})}$.

WEB APPENDIX B

Robustness Checks

In the hypotheses and model development, we fix that the effect of displays on purchase incidence to be positive based on the assumption that every location of product display catch consumers' attention and increase purchase likelihood. However, when it comes to brand choice, the increased purchase intention may lead buying other brands but not the displayed brand. To account for the case, we did not restrict the effect of displays on brand choice probability to be positive. For empirically testing the assumption, we build two alternative models, one with the restrictions on both choices and the other without the restrictions on both choices. Furthermore, we develop another model where the two end cap displays are combined into one for interactions. Model fit is evaluated by deviance information criterion (Spiegelhalter et al. 2002). We also compute the hit rate, which is the posterior mean of the correct prediction for the purchase incidence probabilities for both estimation and holdout samples (the last five weeks, from week 38 to 42). Among the four models, the one with restricted parameters for purchase incidence and non-restricted parameters for brand choice and with separate interactions of end cap displays outperforms the other three, confirming that the proposed model theoretically and empirically supports our assumption.

TABLE WB1. Model Fit Statistics

		Model 1	*Model 2*	*Model 3*	*Model 4*
Positive parameters of displays on	Purchase Incidence	-	√	√	√
	Brand choice	-	√	-	-
Separate interaction parameters of end cap displays		-	-	-	√
Estimation sample	DIC	842304.4	800036.5	784326.5	722540.6
	Hit rate	0.761	0.809	0.842	0.85
Holdout sample	DIC	84412.44	82192.84	77193.81	60723.31
	Hit rate	0.75	0.794	0.82	0.837

WEB APPENDIX C

TABLE WC1. Posterior Estimates for the Endogeneity Specification

Variable	*Brand*	*Mean*		*Standard Deviation*	
		Intercept	*Lagged Value*	*Intercept*	*Lagged Value*
Store front displays	*Coke*	0.001	0.145	0.154	0.148
	Pepsi	0.008	**0.304**	0.151	0.175
	Dr.Pepper	**0.744**	**0.628**	0.262	0.273
	Private brand	**0.653**	0.001	0.199	0.145
Store rear displays	*Coke*	**1.053**	**1.123**	0.281	0.258
	Pepsi	**0.735**	**0.462**	0.286	0.165
	Dr.Pepper	0.045	0.029	0.146	0.142
	Private brand	0.009	0.029	0.139	0.143
Secondary displays	*Coke*	0.044	0.233	0.154	0.155
	Pepsi	0.083	0.001	0.142	0.131
	Dr.Pepper	0.103	0.018	0.142	0.139
	Private brand	-0.009	0.005	0.14	0.146
Front endcap displays	*Coke*	0.003	0.012	0.303	0.327
	Pepsi	-0.023	-0.012	0.321	0.315
	Dr.Pepper	**0.878**	**0.918**	0.056	0.055
	Private brand	**0.867**	**0.737**	0.065	0.066
Rear endcap displays	*Coke*	-0.016	**0.581**	0.239	0.097
	Pepsi	0.179	0.001	0.208	0.294
	Dr.Pepper	0.179	0.003	0.161	0.303
	Private brand	-0.006	-0.022	0.327	0.321
Shelf displays	*Coke*	0.034	0.179	0.318	0.154
	Pepsi	-0.009	**0.68**	0.323	0.061
	Dr.Pepper	**0.734**	**0.748**	0.069	0.084
	Private brand	**0.561**	0.016	0.095	0.315
Discount	*Coke*	-0.009	-0.007	0.139	0.143
	Pepsi	-0.01	0.001	0.157	0.148
	Dr.Pepper	**0.531**	0.366	0.3	0.282
	Private brand	**0.512**	**0.443**	0.298	0.178
Price	*Coke*	**0.802**	**0.664**	0.052	0.061
	Pepsi	**0.805**	**0.521**	0.062	0.082
	Dr.Pepper	-0.016	0.005	0.305	0.294
	Private brand	0.003	0.006	0.325	0.304

TABLE WC2. Variance–Covariance Matrix for the Endogeneity Specification

		Incidence	Brand choice				SCDR				STFR				STRR				FCAP				RCAP				SHLF				DISC				PRICE			
			CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB	CK	PS	DP	PB
Incidence		**1.019**																																				
Brand choice	CK	0	**1.018**																																			
	PS	-0.002	-0.001	**1.016**																																		
	DP	-0.001	0.001	0.003	**1.018**																																	
	PB	-0.001	0.003	-0.001	-0.001	**1.018**																																
SCDR	CK	0.005	0	0.004	0.001	-0.004	**1.048**																															
	PS	0	0.002	0.002	0.001	0	0.03	**1.035**																														
	DP	0.004	0	0.005	0.003	-0.001	0.027	0.033	**1.036**																													
	PB	0.001	-0.005	0	0.005	-0.007	0.016	0.019	0.014	**1.048**																												
STFR	CK	-0.001	-0.001	-0.003	-0.001	-0.001	0	-0.002	-0.002	-0.001	**1.006**																											
	PS	0.002	0	0.002	0.002	0.001	0.002	0.007	0.012	0.001	0	**1.027**																										
	DP	-0.001	-0.001	-0.001	0.001	-0.001	0	-0.003	-0.001	0.001	0.001	-0.001	**1.008**																									
	PB	-0.002	0	-0.001	0	0	0.002	0	-0.001	-0.001	0.002	0.001	-0.002	**0.999**																								
STRR	CK	0.002	-0.002	0.001	-0.002	-0.002	0.007	-0.002	-0.001	0	0	0.001	0.001	-0.002	**1.011**																							
	PS	0.001	-0.001	-0.001	0	-0.001	0	0.002	-0.002	0	0	0	0.002	-0.002	-0.001	**1**																						
	DP	0.001	0.001	-0.001	0	-0.002	-0.001	-0.001	-0.002	-0.002	0.001	0.001	0.001	-0.001	0	0.002	**0.999**																					
	PB	0.001	0	-0.001	-0.002	0	0.002	0	-0.001	0	0.001	0.001	0.001	-0.001	0	-0.001	0.001	**1.001**																				
FCAP	CK	-0.001	0	0.001	0.003	0.001	0	0	0.002	0.001	0.001	-0.001	-0.002	-0.001	0.001	0	0	0	**1.001**																			
	PS	-0.002	0	0.002	-0.001	-0.001	-0.001	-0.002	0	0	0	-0.002	-0.001	-0.001	-0.001	-0.003	-0.001	0	0	**1.015**																		
	DP	0	0	-0.001	-0.001	-0.002	-0.003	0.001	-0.001	-0.002	-0.001	-0.002	0.001	-0.002	0.001	0	-0.001	0.001	-0.001	0	**1.004**																	
	PB	0.001	0.004	0.001	-0.001	0	0	0.001	0.002	-0.004	0.001	0.009	-0.001	-0.002	0	-0.001	0	0	-0.001	-0.004	0.003	**1.041**																
RCAP	CK	-0.001	-0.002	0.005	0.003	-0.004	0.023	0.023	0.02	0.022	0	0.003	0.001	0.002	-0.004	0.002	-0.001	0	-0.002	0.004	0	-0.004	**1.057**															
	PS	0.002	0.001	0.001	-0.003	-0.001	0.004	0.004	0.003	0	0.001	0.001	0.002	0	0.002	-0.001	-0.002	0.003	0.001	-0.001	0	0.003	-0.002	**1.025**														
	DP	0.005	0.004	0	-0.001	0.002	0	0.004	0.008	0.004	-0.001	-0.006	0.003	0.001	0	0.002	0.001	0	0.001	-0.008	-0.001	0.008	0.007	0.001	**1.031**													
	PB	-0.001	-0.001	-0.002	-0.002	-0.001	0	0	-0.002	-0.001	0.002	0	0.002	0.001	-0.001	-0.002	-0.001	-0.002	0	0	0.001	-0.002	-0.002	0	-0.002	**0.999**												
SHLF	CK	0.001	0	0.003	-0.002	0.002	0.015	0.015	0.012	0.009	0	-0.002	0.004	0.002	-0.002	0.001	0.002	-0.002	0	-0.006	0.002	0.001	0.018	0.006	0.009	0.001	**1.031**											
	PS	0.004	-0.001	-0.001	-0.002	-0.005	0.019	0.016	0.012	0.01	-0.003	-0.006	0.003	-0.001	-0.009	-0.001	0.002	0	0.002	-0.007	-0.001	0.014	0.029	0.002	0.017	0.001	0.02	**1.075**										
	DP	0.002	0.002	0.001	0.002	0.002	0.011	0.017	0.01	0.01	0	0.003	0	0.001	0.003	-0.001	-0.001	0	0.002	-0.01	-0.001	0.008	0.009	0.006	0.001	-0.002	0.014	0.025	**1.046**									
	PB	0.001	-0.001	-0.002	-0.003	0.003	0.02	-0.002	0	-0.005	0.002	-0.007	0.006	-0.002	0.011	0	-0.001	0	0	-0.005	-0.001	-0.006	0.001	0.002	0.001	-0.003	0.001	-0.002	-0.006	**1.057**								
DISC	CK	0.001	0.002	-0.001	-0.001	0.001	0.002	0.002	0	0.003	0.001	0.003	0.002	0	0	0	0.001	0	0	-0.001	0.001	0	0.001	0	-0.002	0	-0.001	-0.001	-0.002	0.001	**1.001**							
	PS	0	-0.002	0.001	0	0.001	0.001	0	0.002	0.002	-0.001	0.001	-0.001	-0.001	-0.001	0.003	0	-0.001	0	0.001	0.001	0	0	-0.001	0	0	0.001	0.002	0.001	0	-0.002	**1.001**						
	DP	0	0.001	-0.001	-0.001	0	-0.001	0.001	-0.001	0	0	0.002	0	0	0.002	-0.002	-0.001	0	-0.003	0.001	0	0	-0.001	0.001	-0.001	-0.002	0	0.001	0.001	-0.001	-0.001	0.001	**1.001**					
	PB	-0.001	0	0	-0.001	0	-0.001	-0.002	0.002	-0.001	-0.002	0	-0.002	-0.001	0.001	-0.001	0.001	0.001	0	0.001	-0.001	0.001	0	-0.002	0.001	0	0	0	-0.001	-0.002	0.001	-0.001	0	**0.997**				
PRICE	CK	0	0	-0.001	0.001	-0.001	0.001	-0.002	0	0	-0.001	0	0.001	0.001	-0.001	0.001	-0.002	0.002	0	-0.001	-0.001	-0.001	0	0.002	0.001	0.001	-0.003	0.001	-0.002	0	-0.001	0	0.001	0.002	**0.999**			
	PS	-0.001	0	-0.002	-0.001	-0.001	0.002	-0.001	0.001	-0.001	0.002	0	0	-0.001	-0.002	0.001	0	-0.003	0	-0.002	0.002	-0.002	0	-0.002	0.002	0.001	-0.001	0	-0.002	0.001	0.003	-0.002	0	0.001	0	**1.003**		
	DP	0	0.001	0.001	0	-0.001	-0.002	-0.002	-0.001	-0.001	0	0.001	0	0.001	0	-0.001	0.001	-0.001	0.001	0.001	0.001	0	-0.001	-0.003	-0.001	0.001	0	-0.001	0.003	-0.001	-0.001	0	-0.001	-0.001	0.001	-0.001	**1**	
	PB	-0.002	0	-0.001	0.002	0	-0.001	-0.001	0	-0.001	0.001	0.001	0	-0.001	0.001	0.002	0.002	0	-0.002	0	-0.002	0.001	0.001	0.001	0	0	0.002	0	0	0.001	0.001	-0.002	0.001	0.001	0	-0.001	0	**1.002**

Note: CK, PS, DP, and PB stand for Coke, Pepsi, Dr.Pepper, and Private brand respectively.

WEB APPENDIX D

Optimal Allocation Approach

We now propose one such approach for better allocating the six displays to the four brands compared to the observed pattern in the data. We frame this as a constrained optimization problem. The objective function to be maximized is the revenue and is given as:

$$\text{(WD1)}\ R = \sum_{j=1}^{J}\left[\sum_{i=1}^{N} P_i^{DISP_{dj}}(inc)\cdot\sum_{i=1}^{N} P_i^{DISP_{dj}}(j\,|\,inc)\cdot\overline{PRICE_j}\cdot\overline{Q_j}\right]$$

where $P_i^{DISP_{dj}}(inc)$, $P_i^{DISP_{dj}}(j\,|\,inc)$, $\overline{PRICE_j}$, and $\overline{Q_j}$ for brand *j* and customer *i* are the purchase incidence probability, brand choice probability, mean price per ounce and mean purchase quantity respectively. Since the primary focus is to maximize the retailer's revenue, we compute the sum of the revenues across all *J* brands. Our approach to obtain the optimal number of displays for each display brand combination involves incrementing each display type for each brand and computing the overall revenue. For example, we increment the revenue for brand 1 and display location 1 in unit step sizes and compute the revenue across all brands and all displays based on equation WD1 (subject to constraints described below). The optimal number of displays ($DISP_{11}^{*}$) for brand 1 and display location 1 is obtained based on the combination that maximizes the overall revenue. Specifically, we solve the following maximization problem:

$$\begin{aligned}
&DISP_{dj}^{*} = \max_{DISP_{dj}}(R(\{DISP_{dj}, DISP_{-(dj)}\}))\\
\text{(WD2)}\qquad &\text{s.t. } R(\{DISP_{dj}, DISP_{-(dj)}\}) > R(DISP^{observed}),\\
&\text{and}\quad 0 \le DISP_{dj} \le \sum_{j=1}^{J} DISP_{dj}^{observed} - \sum_{k=1}^{j-1} DISP_{dk}^{*} - \sum_{l=j+1}^{J} DISP_{dl}^{observed}
\end{aligned}$$

where, $DISP_{dj}^{*}$ is the optimal number of displays for display *d* and brand *j*; $R(\{DISP_{dj}, DISP_{-(dj)}\})$ is the revenue evaluated for the focal display *d* and brand *j* ($DISP_{dj}$) and all other displays $DISP_{-(dj)}$. $DISP_{-(dj)}$ consists of both the computed optimal number of displays for display *d* for brands that precede brand *j* and the observed number of displays for brands that succeed brand *j* and is given by:

$$\text{(WD3)}\ DISP_{-(dj)} = \{DISP_{11}^{*},\cdots,DISP_{d-1,J}^{*}, DISP_{d1}^{*},\cdots,DISP_{d,j-1}^{*}, DISP_{d,j+1}^{observed},\cdots,DISP_{DJ}^{observed}\}$$

Our approach assumes that the total number of displays at a specific location as given or determined by the retailer and does not attempt to change that number. However, our proposed optimization scheme reallocates the total number for each type of display across different brands with an aim to maximize revenue. Hence, $\sum_{j=1}^{J} DISP_{dj}^{observed} = \sum_{j=1}^{J} DISP_{dj}^{*}$.

Starting from the first brand and first display type, we estimate the parameters using the number of displays given by $\{DISP_{dj}, DISP_{-(dj)}\}$ along with other variables and use the result to calculate the corresponding choice probabilities and resulting revenue from equation WD1. We then increase $DISP_{dj}$ in steps of 1 and find the optimal solution, $DISP_{dj}^{*}$, which yields the highest revenue. Within a specific type of display *d*, the upper bound for $DISP_{dj}$ is conditional on the observed and optimal number of display *d* for the other brands. Our proposed approach, therefore, provides a conservative estimate for the optimal number of displays and increment in revenue. In other words, instead of a global solution that generates all possible combinations of $DISP_{dj}$ across *j* brands for each display *d* and evaluates them in terms of the revenue, our proposed solution proceeds sequentially optimizing each brand-display combination. This approach is similar to subgame perfect (Sun 2005) and is efficient in that it can reduce the number of combinations and the time it takes[8] to obtain the optimum values.

After sequentially going over each display-brand combination and solving equation WD2 for every display and brand, we obtain an optimal solution $DISP^{*}$ and the revenue R^{*} given by:

$$\text{(WD4)} \quad DISP^{*} = \{DISP_{11}^{*}, \cdots, DISP_{dj}^{*}, \cdots, DISP_{DJ}^{*}\}$$

$$\text{(WD5)} \quad R^{*} = R(DISP^{*})$$

Category captain revenue maximization

The objective function to be maximized is the revenue of brand *j* in charge of managing marketing activities of the category and is given as:

$$\text{(WD6)} \quad R_j = \sum\nolimits_{i=1}^{N} P_i^{DISP_{dj}}(inc) \cdot \sum\nolimits_{i=1}^{N} P_i^{DISP_{dj}}(j \mid inc) \cdot \overline{PRICE_j} \cdot \overline{Q_j}$$

Then the maximization problem can be defined as:

[8] For example, in week 6, there are about 9 million possible combinations for brand and display in increments of 1 to obtain a global optimum and each combination requires at least 30 minutes for parameter estimation and revenue optimization.

$$DISP_{dj}^{*} = \max_{DISP_{dj}} (R_j(\{DISP_{dj}, DISP_{-(dj)}\}))$$

$$\text{(WD7)} \qquad \text{s.t. } R_j(\{DISP_{dj}, DISP_{-(dj)}\}) > R_j(DISP^{observed}),$$

$$\text{and} \quad 0 \le DISP_{dj} \le \sum_{j=1}^{J} DISP_{dj}^{observed} - \sum_{k=1}^{j-1} DISP_{dk}^{*} - \sum_{l=j+1}^{J} DISP_{dl}^{observed}$$

Similar to optimizing retailer revenue, the optimal solution $DISP^{*}$ and the revenue of brand j (R_j^{*}) are obtained after sequentially going over each display-brand combination and solving equation WD7 for every display and brand. The optimized revenue R_j^{*} is given by:

$$\text{(WD8)} \quad R_j^{*} = R_j(DISP^{*})$$

where the optimal solution $DISP^{*}$ has the same notation as equation WD4.