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Three Essays on Optimization and Decision-Making Solutions in Grocery Retail Operations

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Dedication

With admiration and gratitude to Mark Ferguson, Michael Galbreth, Olga Perdikaki, Su-Ming Wu, and Pelin Pekgun.

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Abstract

In this dissertation titled "Three Essays on Optimization and Decision-Making Solutions in Retail Operations," we explore various techniques aimed at optimizing the operational efficiency in a grocery retail store. Specifically, the first essay examines a store manager's decision of which stock-keeping units (SKUs) from a given category to assign to a promotional display space. We develop a decision support tool that consists of an estimation model and an optimization model. Using a grocery store sales transaction dataset, we introduce a methodology to measure the incremental lift in sales of placing a particular SKU on promotional display space. Our optimization model includes the incremental lifts (from the estimation method) combined with the estimated base-sales rates and profit margins of each SKU so that the profit-maximizing SKU can be chosen for a promotional display space for each week of the year.

The second essay offers a novel methodological solution on the appropriate identification and analysis of submarkets in product categories. Our research contributes to the literature in the following ways. While a vast amount of literature in both marketing and operations management investigate retail decision tree structures, limited information exists on developing algorithms that allow to generate, analyze, and test data-driven decision trees. Understanding how decision trees may drive consumer preferences is critical to a retailer's choice of product category assortment. We provide a methodology on empirically constructing and evaluating the best fitting decision tree structures using easily accessible and readily available scanner data.

The third essay studies the mechanisms retailers can use to facilitate sales of reduced packaged products, which have a number of advantages that are attractive to retailers, manufacturers, and consumers. Large product packaging creates logistical and operational challenges for retailers who carry such products since these products require more space to be stored and displayed, and more manpower to handle it. In contrast, products in smaller packaging have fewer such problems, and, thus, positively contribute to the retailer's operational efficiency. We discuss and empirically test two levers that retailers may utilize to influence the sales of reduced packaged products. Using sales data for liquid detergents, we show that retailers with market power are able to announce their preferences for reduced packaged detergents, which results in an industry-wide shift toward reduced packaged detergents. We also show that retailers, with varying degrees of market power, may select higher ratios of reduced packaged detergents and achieve convex levels of sales of reduced packaged detergents.

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Introduction

As brick-and-mortar merchandise and apparel retailers experience a sharp decline in the era of Amazon's domination [Thompson, 2017], grocery retailers, on the other hand, continue to strive. In fact, the grocery store sector is one of the dominant players in the US retail industry. As of August 2019, monthly food sales at traditional grocery stores are estimated at $57 billion [US Census Bureau, 2018b], and $6.74 trillion worth of grocery products were sold at US grocery stores in 2018 alone [US Census Bureau, 2018a]. As one industry expert puts it, customers still "want to squeeze the melon" with their bare hands, and "they [still] want to see the cuts of meat" before their own eyes when making a food-related purchase [Anders, 2017]. The fact that online stores cannot provide such experiences can perhaps explain the strong financial performance of the brick-and-mortar grocery sector.

It is well established that "product variety and relevance is a fundamental driver of consumers' purchase decisions, and ultimately of a retailer's profitability" [Saure, 2012, p.1]. Thus, to maintain a competitive advantage over fellow brick-and-mortar rivals, one of the biggest operational challenges of traditional grocery stores is to determine a product assortment that is optimally efficient. Competition from discount stores like Aldi, Lidl, and Trader Joe's, evolving tastes and preferences of a modern consumer, and rapid proliferation of product assortment—only complicate this task. The chapters in this dissertation are dedicated to helping modern retailers make efficient assortment decisions.

The first essay offers a novel methodology to optimize the product selection for promotional endcap display that allows a local store manager to estimate the relative lift of an SKU on promotional display and develop an optimization framework to identify the most display-profitable products. Specifically, we show how a store manager can short-list the potential SKU candidates to put on promotional display and offer an estimation methodology that allows them to estimate the relative lift of an SKU on promotional display. We then develop an optimization framework to identify the most profitable SKUs to display. The key parameter is the estimated incremental lift in sales from each SKU candidate being placed on a promotional display. Our methodology also requires an estimate of each SKU candidate's base demand–the demand an SKU will achieve in the absence of any price, feature (such as weekly flyers) or display space promotions. The expected incremental profit from placing each SKU candidate on promotional display is then calculated by multiplying the base demand with the incremental sales lift from being placed on a promotional display space with the profit margin of that SKU. For a single promotional display space, such as an endcap, the profit-maximizing SKU within the pre-selected product category is then selected for each week of the planning horizon.

The second essay focuses on attribute-based competitive market structures of products to help retailers make optimal product assortment decisions. We develop a systematic, data-driven methodology to empirically identify attribute-based product demand structures, also known as decision trees to identify a "stylized" process by which a typical decision-maker arrives at a decision [Shocker et al., 1991, p.182] using retail scanner data. Typically, market structure analysis seeks to identify a "stylized" process by which a typical decision-maker arrives at their final product choice [Shocker et al., 1991, p.182]. This is not an easy task given that not all attributes are created equal in terms of their importance to the customer, and that the competition between products increases as their attributes become more similar [Rao and Savabala, 1981]. Previously used methods to identify market structures like consumer surveys, focus groups, or individual manufacturer analysis not only use a limited scope of data, which can paint an incomplete picture about true market structures but also they are not algorithm-friendly. In contrast, this work develops algorithms that use historic sales data to determine, analyze, and visualize market structure at a category level in the form of decision trees.

The last essay also utilizes scanner data and explores the relationship between reduced packaged products and their sales. Amidst ongoing product assortment expansion (modern retailers can carry up to 300,000 SKUs [Breuer et al., 2013]) and 'rapidly shrinking stores' [Bhattarai, 2017, Tuttle, 2014], oversized packaging creates a logistical challenge for retailers. Oversized packaging is inefficient: it requires more space to be stored and displayed and more manpower to handle it, thus, potentially affecting the retailer's ability to achieve operational efficiency [Hellstrom, 2007, Goldsby and Martichenko, 2005]. The overall transition to reduced packaged products through product concentration has proven to be a challenging task.

To address this challenge, we are exploring ways of how retailers can use their own levers of power to fix this problem. We distinguish between two distinct levers—one that retailers with significant market power may exert, and another that is available to a broad range of retailers, including those with relatively less market power. The first lever is wielded by retailers with significant market power. Specifically, we look at Walmart's announcement officially mandating all US and Canadian detergent producers to supply concentrated versions of their products and its impact on the detergent industry. As levers go, this is a rather direct one, primarily aimed at manufacturers.

However, few retailers have the power to replicate Walmart's impact. A lever that they can utilize, alternatively, is to incorporate nudging toward certain product choices or product characteristics, an economic theory well-summarized and widely popularized by Thaler and Sunstein [2009]. "A nudge is a term used to describe any change in the environment, which steers an individual's behavior in a predictable way while preserving their freedom of choice. It's not a push nor a shove, but a gentle nudge" [Catchpole, 2018]. This notion is yet to be sufficiently explored in a retail operational context, and as recently underscored by Donohue et al. [2019], is a promising choice architecture technique to improve decision processes and outcomes in operations research.

Chapter 1

Optimizing Stock-Keeping Unit Selection for Promotional Display Space at Grocery Retailers

1.1 Introduction

The grocery store sector is one of the major players in the US retail and foodservice industry. In 2018 alone, its total seasonally adjusted annual sales approached $6.8 trillion [US Census Bureau, 2018a]. Grocery store managers have several operational and marketing levers at their disposal to increase the profitability of their stores. Operational levers include store layout, the product assortment, and the stocking/replenishment policies while marketing levels include the pricing and promotion of the products that were previously selected in the assortment decision. While all of these levers have received considerable attention in the academic literature, there is an additional lever at the operations/marketing interface that has been mostly overlooked – optimizing the product selection for which stock-keeping units (SKUs) to place on a limited amount of promotional display space. This lack of attention is surprising because an increase in product exposure is known to result in one of the most coveted shopper outcomes, persuading the shopper to make impulse purchases (purchases of products that the shopper did not originally plan on purchasing) of full-priced products [Kollat and Willett, 1967, Inman and Winer, 1998].

It is well understood within the grocery industry that impulse purchases are driven by product exposure. Common impulse buy items such as candy and magazines are almost universally placed near the checkout lanes of most national grocery store chains. A recent industry study of two million grocery store shoppers shows that products placed on a promotional display are seen by nearly twice as many store visitors as products that are located in the inner aisles of the store [Wade, 2014]. Promotional display space increases product visibility [Garrido-Morgado and Gonzalez-Benito, 2015] and increases the number of impulse buys [Kacen et al., 2012]. Thus, placing a product on promotional display is a very valuable tool for stimulating incremental product sales (via impulse buys) for new or existing products by exposing products to potential customers that may not have originally planned to purchase an item from that particular product category. An example of an unplanned impulse buy is when a father stops by a store to pick up some baby formulae but, upon passing by a promotional display space of beer, decides to include a six-pack of beer in his purchase. Promotional display space includes endcap displays, front walls, wings, display racks, countertops, gondola checkouts, showcases, specialty shelves, dump bins, and dump tables. They are located in high-traffic and high-visibility areas around and on the outside edges of a store's shelf space perimeter.

A typical grocery store perimeter offers fresh, high-margin foods like produce, bakery items, meats, dairy products, and deli [Johnson, 2018]. The center-store aisles are located inside the perimeter and include twelve or more aisles with shelf-stable consumer-packaged goods (CPG) ranging from toiletries to frozen pizzas [Rupp, 2015]. Promotional endcap displays face the perimeter of the store, while other displays can be placed in-between the aisles, the lobby area, or in other high traffic areas of the store [Frazier, 2014]. Recent technological advances like radio frequency identification tags (RFID) attached to retail shopping carts and shopper movement video-reading software show that an overwhelming majority of grocery shoppers shop the perimeter of a grocery store and avoid entering the center aisles [Sorensen, 2008, Shop Association, 2016]. As a result, in contrast to inner-aisle merchandise, products located on the endcaps enjoy substantially more face time [Larson et al., 2005]. A large-scale industry study of millions of grocery shoppers found that products placed on promotional displays receive 93% more exposure than those on the inner aisles of the same store [Shop Association, 2016]. This behavior implies that products placed on endcaps have a much higher probability of driving impulse purchases [Phillips and Bradshaw, 1993, Bezawada et al., 2009, Nakamura et al., 2014], where the lift in sales comes from purchases that are often not combined with a price reduction. Thus, promotional display space does not face the trade-off that other common promotion levers such as price discounting do since the product margins are often maintained and combined with a lift in unit sales.

1.1.1 Problem and Motivation

The choice of which SKUs to place on promotional display space is also very different than the more commonly discussed assortment planning/optimization problem. Assortment optimization is concerned with selecting a subset of products/items to include in a store's assortment among a set of potential candidates, factoring in important issues such as space limitations and potential substitution effects as the demand of an item depends on the presence of other items in the assortment. In contrast, promotional display optimization is concerned with selecting a subset of products/items to place on promotional display from a given assortment that the store already carries. Since the effectiveness of promotional displays relies on generating impulse purchases, frequently changing the products on the promotional displays is necessary for impulse purchases to continue to occur. Hence, while the nature of promotional display optimization is dynamic and may change from week to week, assortment optimization gives recommendations meant to stand for a considerable length of time, as it would be confusing to shoppers to have the store's assortment and shelf contents change as frequently as promotional displays do.

Due to these important differences in the overall objective of the problem, conventional methods for the assortment optimization problem are not appropriate for the promotional display allocation problem for the following reasons: First, promotional display decisions, unlike assortment planning decisions, provide retailers with an important degree of freedom i.e., the ability to adjust a product's visibility, generating impulse buys without changing the overall product assortment. Thus, an important characteristic of a promotional display decision support tool is the ability to measure the effectiveness of promotional display space in terms of generating incremental sales rather than total sales. Second, the nature of substitution that shapes consumer demand is different in assortment planning decisions as compared to promotional display allocation decisions. In assortment planning, an important consideration is consumers' willingness to substitute their original preferred product if it is not offered in the assortment, referred to as assortment-based substitution [Kok and Fisher, 2007]. In the context of promotional display however, substitution arises from the increased visibility that a product achieves when placed in a promotional display relative to a product located in an inner-aisle. Given these distinct differences in the types of substitution, there is a need for distinct methods to address these two types of decisions. Finally, a methodology that can assist with promotional display allocation decisions at a given store location should be able to estimate sales lifts of SKUs that have never been chosen for a promotional display at that particular store. Thus, sales data from a large number of stores is needed to estimate these sales lifts.

Given the low-cost[1] but high-return nature of promotional display space, it is surprising that, while the academic literature and retail software solution providers offer a variety of optimization solutions for the assortment optimization problem [Chong et al., 2001, Kok and Fisher, 2007, Rooderkerk et al., 2013], there is very little guidance for retailers on how to optimally determine when and what products to place on their promotional display space[2]. Consequently, retailers often default to simple heuristics when making this decision, such as selecting the best-selling SKUs or SKUs where the OEM offers the most generous trade allowances for placing their products on promotional displays. In some cases, large grocery chains make the decision at the firm's headquarters, thus imposing the same selection of SKUs across different geographical store locations and time periods. Such heuristics are often far from optimal because some SKUs do not need any additional exposure to continue to be a best-selling SKU and what may be a profitable SKU at one geographic location may not be so at a different location. In the absence of any decision support system to help with this decision, it is difficult to know which SKUs are the most profitable to allocate to a limited number of promotional display locations at each store.

1.1.2 An Overview of our Methodology

Next, we discuss our methodology for providing such a decision support system. While the selection of which product category to put on promotional display is rather

[1] A retailer typically incurs a relatively low cost for building the promotional displays. This is because the manufacturers usually send their own sales representatives to make the displays in the store and the retailer uses its own labor to remove unsold items from the promotional displays during display changes.

[2] A white paper [Wade, 2014] offers a brief overview of possible steps taken by a retailer who seeks to pick items for an endcap display using household-level purchasing data along with their movement-tracking video data. This paper, however, is very high-level and lacks any specifics required for implementation. Additionally, a patent filed by Target discusses placement of products on check-out lane shelves but does not discuss endcap displays [Target Brands, Inc., 2013].

straight forward, given that there are only a small number of product categories that generate significant impulse buying demand (i.e. candy versus toilet paper), choosing a specific SKU from an existing category is significantly more challenging. Thus, we start by assuming that a store manager has already decided which category to place on a promotional display space such as an endcap at his store, and offer an initial effort in filling this research gap by providing a methodology that helps select the profit-maximizing SKU from within this category to place on promotional display for each week[3].

We first discuss how the store manager can short-list the potential SKU candidates (from that store assortment within the pre-selected category) to put on promotional display and offer an estimation methodology that allows him to estimate the relative lift of a SKU on promotional display. Then, we develop an optimization framework to identify the most profitable SKUs to display. The key parameter is the estimated incremental lift in sales from each SKU candidate being placed on a promotional display. Our methodology also requires an estimate of each SKU candidate's base demand – the demand a SKU will achieve in the absence of any price, feature (such as weekly flyers) or display space promotions. The expected incremental profit from placing each SKU candidate on promotional display is then calculated by multiplying the base demand with the incremental sales lift from being placed on a promotional display space with the profit margin of that SKU. For a single promotional display space, such as an endcap, the profit-maximizing SKU within the pre-selected product category is then selected for each week of the planning horizon. When making these selections, we account for two important effects of promotional activities, the category expansion effect, and the cannibalization effect [Blattberg et al., 1995]. Specifically, we incorporate in our estimation model the cross-SKU marketing mix effects among

[3]In Appendix 3.5 we discuss how our methodology can be extended to select SKUs across different product categories to assign on promotional display.

similar SKUs (i.e., the effect of a SKU's marketing mix activities on the demand of other similar SKUs) by using an attribute-based metric to capture the similarity among SKUs [Hardie et al., 1998, Rooderkerk et al., 2013].

To demonstrate our methodology, we use retail CPG sales scanner data from hundreds of grocery stores from both the same, and different, grocery store chains in the New England region of the USA [Bronnenberg et al., 2008][4]. For illustration purposes, we use the transaction data from the beer category (from all grocery chains in New England) to estimate the incremental lifts in sales of placing a particular beer SKU on promotional display. Then we focus on the optimization of a major promotional display (e.g., an endcap) for a given store, chosen randomly from our dataset. We first provide a static optimization framework to illustrate the optimal SKU selection for a promotional display at a weekly level. We, then consider a dynamic version of our optimization framework which identifies, in a single optimization run, the profit-maximizing SKU to be placed on a promotional display over every week in the planning horizon considering several practical aspects such as common business rules that restrict the selection of the same SKU over a consecutive set of weeks, display-related changeover costs, and slotting fees offered by the manufacturers.

1.1.3 Our Findings and Contributions

We find that assigning a SKU on promotional display can result in a significant lift in sales, even in the absence of an accompanying price reduction. For instance, the average estimated sales lift for the beer category is 27%[5], confirming that promotional display is an effective tool for stimulating demand. We then compare the profitability

[4]This dataset includes data from across the U.S. but we only use the data from the New England region because, for beer, preferences are regional.

[5]The sales lift is calculated as $(e^{0.235} - 1) * 100\% \simeq 27\%$.

of our methodology with a common industry benchmark, which selects the best-selling SKUs each week to be placed on a promotional display that same week.

Our work underlines an important contribution to retail practice: an easy-to-implement promotional display SKU-selection methodology that is scalable and meets several of the challenges associated with promotional display SKU-selection. The main novelty of our approach comes primarily from integrating an estimation model with an optimization model which are capable of handling an extensive and complex product assortment and account for effects such as cannibalization of the inner aisle sales and category expansion, considerations typical in promotional activities. Additionally, our optimization model is flexible enough to consider different practical aspects such as common business rules that restrict the selection of the same SKU over a consecutive set of weeks, display-related changeover costs, and slotting fees offered by the manufacturers.

Our work also underlines an important contribution to theory. It demonstrates that even though there is a trend to focus on a more disaggregate level of analysis (e.g., store-level analysis), there is need to sometimes take a more aggregate view (region level versus store level or chain level) to estimate some effects that do not occur frequently enough at the less aggregate level. The marketing literature focused on estimating price and promotion effects has lately moved in the direction of a less aggregate level of analysis. A number of papers, for example, focus on micro-marketing i.e., the customization of marketing mix variables to the store level (e.g., Montgomery [1997]). Store-level control of the marketing processes is very important and micro-marketing has been identified as one of the best marketing practices based on a case study analysis of major retailers [Ziliani and Bellini, 2004]. Despite the evident value in this less aggregate level of analysis, some effects can only be measured at the aggregate level. Our study provides a good example where a less aggregate level of analysis is appropriate (and even required) to capture certain effects that do not occur frequently enough at a single location. The effect of placing SKUs on promotional display, for instance, can only be measured at the aggregate level given that most SKUs have never been put on display at a given store. This is due to the very large number of SKUs that a typical grocery retailer carries compared to the small number of promotional display spaces available.

The rest of the paper is organized as follows. In Sect.ion 1.2, we review the relevant literature. In Secti.on 1.3, we describe our methodology. In Section 1.4, we describe the data that we use to illustrate our methodology. In Section 1.5, we apply our methodology using our dataset and assess its performance. In Section 1.6, we conclude the paper.

1.2 Literature Review

We propose a decision support tool to assist with promotional display allocation decisions for grocery retailers. There has been a long history in the operations management literature of providing decision support systems in different areas such as service locations [Narasimhan et al., 2005], supply chain design and process design [Blackhurst et al., 2005], and facility network design [Robinson Jr. and Swink, 1995].

The two areas of the operations and marketing literature that are the most closely related to our work focus on the product assortment and promotion planning decisions. To date, however, their primary focus has been on sales that occur from placement on inner-aisle (i.e. non-promotional) shelf space [Wan et al., 2012, Ketzenberg et al., 2000, Patel and Jayaram, 2014, e.g.,] rather than the promotional shelf space. Since our methodology provides a decision support tool that includes an estimation component (in addition to an optimization component), we focus our review on other papers that provide a similar comprehensive solution. Thus, we do not include discussions of papers (except an analytical paper by Cetin et al. [2018]) that do not include an estimation procedure. Figure 1.1 summarizes the attributes of select relevant studies that include both estimation (with an exception of Cetin et al. [2018]) and optimization components with those of our own. For a more comprehensive review of the product assortment literature, we refer the reader to Kok et al. [2015] and of the promotion literature – to Gedenk et al. [2006].

Table 1.1: Select Literature

Characteristics \ Study	Kok and Fisher (2007)	Rooderkerk et al. (2013)	Collado and Martinez-Albeniz (2014)	Chong et al. (2001)	Hubner and Schaal (2017b)	Fisher and Vaidyanathan (2014)	Cohen et al. (2014)	Baardman et al. (2015)	Ma and Fildes (2017)	Natter et al. (2007)	Cetin et al. (2018)	This study
AREA:												
Product assortment	✔	✔	✔	✔	✔	✔						
Promotion							✔	✔	✔	✔		
Product assortment for promotional display									✔		✔	✔
STORE AREA:												
Regular shelf-space	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔		
Promotional shelf-space									✔		✔	✔
UNIT OF ANALYSIS:												
SKU-level	✔	✔	✔		✔	✔			✔	✔	✔	✔
Brand-level				✔			✔	✔				
Category-level											✔	
MODEL DETAILS:												
Choice	✔		✔	✔		✔					✔	
Linear/loglinear		✔			✔				✔	✔		✔
Other nonlinear							✔	✔				
INDEPENDENT VARIABLES												
Price	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔		✔
Week effect	✔	✔	✔	✔			✔	✔	✔	✔		✔
Advertisement/feature effect		✔		✔					✔	✔		✔
Display effect		✔		✔					✔			✔
Display-Week effect												✔
Discount effect									✔			✔
Not applicable											✔	
DATA SOURCE:												
Single store	✔											
Single retailer		✔	✔	✔	✔		✔	✔	✔	✔		
Multiple retailers						✔						✔
None											✔	

1.2.1 Decision Support Tools for Product Assortment Decisions

Assortment optimization is concerned with selecting a subset of products to include in an assortment among a set of potential candidates. A properly chosen product assortment has been postulated as a key element of a store's commercial success [Levy and Weitz, 2004, Fox et al., 2004].

Since our work is a decision support tool, we do not elaborate on previous works in assortment optimization/planning whose contribution rests solely on analytical or numerical studies [e.g., Anderson and Amato, 1974, Borin et al., 1994, Urban, 1998, McIntyre and Miller, 1999, van Ryzin and Mahajan, 1999, Mahajan and van Ryzin, 2001a,b, Agrawal and Smith, 2003, Cachon et al., 2005, Gaur and Honhon, 2006, Cachon and Kok, 2007, Caro and Gallien, 2007]. Instead, we review studies that provide decision support tools for assortment optimization that include both estimation and optimization components, as our goal is to fill the void in the literature by introducing a *SKU-selection* decision support tool for a *promotional* shelf space (like endcap displays). Kok and Fisher [2007] propose a SKU-specific product assortment optimization by developing an iterative heuristic in the form of a knapsack problem. Rooderkerk et al. [2013] use store-level scanner data to develop an attribute-based demand estimation model and a profit-maximizing product assortment heuristic. Chong et al. [2001] develop a nested multinomial logit (NMNL) model to identify the optimal brand-level product assortment and use household shopping data to estimate the model. Boada-Collado and Martínez-de-Albéniz [2014] offer a variation of Kok et al.'s (2015) assortment planning problem by optimizing SKU-level assortment using choice modeling in a multi-period setting. Fisher and Vaidyanathan [2014] present a product assortment decision support tool for completely new SKUs that have never been carried before. Other studies have added a shelf space dimension to the assortment problem. For example, Hubner and Schaal [2017] maximize a retailer's profit by simultaneously choosing the assortment and shelf-space under stochastic and space-elastic demand.

Our work differs in its overall objective (i.e., the selection of SKUs from a given assortment to be placed on a promotional display space) from all of the works described above. Our methodology is also distinct in that we estimate the relative lift of placing a SKU on promotional display and then develop an optimization framework to identify the SKUs that generate the highest incremental profit from a given assortment that the store already carries.

1.2.2 Decision Support Tools for Promotion Decisions Other Than Display

Another relevant stream of literature focuses on price-promotion planning, where various methodologies are proposed to make price-promotion scheduling more cost-effective and profitable. Cohen et al. [2017] develop a profit-maximizing price promotion optimization problem and show that their optimized promotion schedule can improve a retailer's profit by 3%. Baardman et al. [2018] model flyer and TV commercial promotions decisions as a non-linear bipartite matching-type problem. Their optimized promotion assignments result in up to 9% profit improvement. Natter et al. [2007] provide a decision support tool for price promotion activities. An actual business implementation of their solution leads to their partner's profit and sales increase of 8.1% and 2.1%, respectively. Other relevant work in the marketing area includes Allenby [1989], Ailawadi et al. [2006], Ailawadi et al. [2007], Dawes [2012], and Gong et al. [2015].

An important feature of all of the works described above is that these studies treat promotion as a price-based event (i.e. to promote a product, a necessary price reduction is involved). In contrast to such studies, display promotions do not necessarily involve price reductions but rely on the higher visibility of promoted products to motivate impulse buys. Thus, whereas price discounts can attribute to pantry loading practices which cannibalize future sales, promotional displays primarily drive current impulse purchases.

1.2.3 Decision Support Tools for Promotion Display Decisions

To the best of our knowledge, there are two prior studies that focus on promotional display allocation decisions. Ma and Fildes [2017] develop a SKU level promotions planning optimization method. They aim to simultaneously optimize three different types of promotional activities such as price, display, and feature advertising. Our work differs from Ma and Fildes [2017] along some very important dimensions. They develop and estimate their demand model at the store level which can *only* capture and measure the sales lifts of those SKUs that have been placed on promotional display at a given store location. As a result, their model can only evaluate and recommend SKUs that have been put on display at a given store which can be restrictive given that most SKUs (even within the same product category) will have never been put on display at a single store location due to the small number of promotional display spaces available. We, on the other hand, propose an estimation method that considers different stores within a grocery chain and across different grocery chains in order to measure such effects (i.e, the sales lifts from placing different SKUs on promotional display) that do not occur frequently enough at a single location[6]. In addition, they only estimate the display effect at the aggregate level, as opposed to the week-SKU level[7]. In contrast, our estimation model captures the display effects at the SKU-week level so that our proposed decision support tool can recommend a promotional display schedule (i.e., SKU selection and timing) over every week in the planning horizon.

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[6]Our data actually supports the scarcity of display decisions for a given category at the store level. For example, at a randomly selected store in our dataset, only twelve out of 334 beer SKUs were placed on promotional display throughout the year as shown in Table 1.8.

[7]Note that the coefficient in Ma and Fildes [2017] for the display lift does not contain a subscript for a specific week but rather a subscript for the current and past week.

Another related study on promotional display decisions is the work by Cetin et al. [2018] who propose a stylized optimization model but no estimation procedure. Cetin et al. [2018] assume a given nested multinomial logit, which is later used in a two-step promotional display decision (first picking an optimal product from a given category, and later across categories). They show that low popularity/high margin products are better candidates for promotional displays in order to promote impulse buys, whereas high popularity/low margin products should be kept in the store's inner-aisles. We don't classify their approach as a decision support tool because no evidence is provided on how to estimate the parameters needed for their stylized model.

Our paper offers a decision support system to help select the most profitable SKUs to allocate to a (constrained) promotional display space capacity at a particular store location. Like some product assortment planning [Rooderkerk et al., 2013] and promotion planning [van Heerde et al., 2004, Foekens et al., 1994] papers, we build on the Scan*Pro estimation model [Wittink et al., 1988]. This regression-type log-linear model is one of the first models to uncouple the impact of display on sales from other marketing mix activities[8]; and one of the most commonly used models in industry applications because it can be estimated in a reasonable amount of time, even for very large datasets, such as the multi-store, multi-location dataset that we use in our study. The Scan*Pro model also allows us to control for the influence of various price and marketing mix variables on product sales in addition to cross-product effects.

In line with Cetin et al. [2018], who assume that a promotional display can have a category expansion effect and a cannibalization effect, we also account for these effects in our empirical estimation. Specifically, we model cross-SKU marketing mix effects, which can be positive or negative, among similar SKUs and capture similarity among

[8]Another early model to uncouple the impact of display on sales from other marketing mix variables is Blattberg and Wisniewski [1987]; however, this model is aggregated at the brand and price zone level for a chain, and the display is defined as the number of stores displaying the brand.

SKUs through an attribute-based metric [Hardie et al., 1998, Rooderkerk et al., 2013]. Our methodology also includes an optimization step that selects the optimal SKU from an existing store's assortment to put on promotional display for each week in the planning horizon.

1.3 Methodology

We begin with the assumption that store managers have already established a set of displays devoted to particular product categories[9]. Hence, given a category, we propose a methodology that identifies the profit-maximizing SKU from within this category to place on promotional display for each week. We first propose an estimation methodology that allows a local manager to estimate the relative lift of a SKU on promotional display and then develop an optimization framework to identify the most profitable SKU to display. Our methodology requires as inputs the estimated incremental lift in sales from each SKU candidate being placed on a promotional display and an estimate of each SKU candidate's base demand (the demand a SKU will achieve in the absence of any promotional activity). The expected incremental profit from placing each SKU candidate on promotional display is then calculated by multiplying the base demand with the incremental sales lift from being placed on a promotional display space with the profit margin of that SKU. For a single promotional display space, such as an endcap, our optimization model selects the profit-maximizing SKU within the pre-selected product category for each week of the planning horizon.

Depending on the size of the pre-selected product category that a store carries, it could be computationally challenging to evaluate all the SKUs within that pre-

[9] Recall that we discuss how our methodology can be extended to determine which SKUs across different product categories to assign to promotional displays in Appendix 3.5.

selected category especially for a large store. In that case, our approach could select a subset of SKUs from different subcategories (within the pre-selected category) to evaluate as potential candidates to put on promotional display. Different rules-of-thumb could be used when selecting the potential SKU candidates. (More details on the different selection criteria is provided in Section 1.5). Since our approach essentially evaluates the different existing subcategories at the same time, it leverages the across-subcategory variation in sales, in addition to the within-subcategory variation, which results in higher efficiency of the estimates and better precision. In situations where the grocery retailers cannot restrict the potential SKU candidates to put on promotional display to a reasonable size, we discuss an alternative approach, called Hierarchical, in Appendix 3.5.

1.3.1 Sales Response Function

To obtain the incremental sales lift, we need an econometric model that can estimate the display effect using store-level data. To do so, we build upon the original Scan*Pro model, which has been used in more than 1,800 commercial applications [Wittink et al., 1988, Foekens et al., 1994]. This model successfully incorporates various promotional instruments, including display, as predictors, and allows the use of syndicated sales scanner data.

We model the demand/sales of SKU $j \in \mathbb{U}$ (the consideration set of SKUs for promotional display) at store i in week t as a log-linear model[10] given in (1.1) to capture the effect of placing SKU j on promotional display (on its sales) controlling,

[10]Our setting precludes the use of choice modeling as an estimation technique due to the following reasons. To estimate a traditional choice model, one must have data on revealed purchases at the individual transaction-level, along with the information on the full choice set of products available to a consumer at that moment [Train, 2003]. Even with a methodology that can accommodate aggregate data for a choice model [Berry, 1994], purchase information still has to be limited in size and scope, with a full choice set usually not exceeding more than 4-5 options. In our setting, the storesâĂŹ transaction data is only collected at an aggregate level (by firms such as

among other factors, for seasonality and marketing-related activities (i.e., discounts, temporary price reductions, advertisements, coupons) at store i during week t.

$$
\begin{aligned}
\ln S_{jti} = {} & \overbrace{\delta_0}^{\text{Intercept}} + \overbrace{\sum_{z \in \mathbb{U}} \delta_{1z} Z_{jz}}^{\text{SKU Effect}} + \overbrace{\delta_2 D_{jti}}^{\text{Display Effect}} + \overbrace{\delta_3 H_{jti}}^{\text{\% Discount Effect}} + \overbrace{\delta_4 P_{jti}}^{\text{Price Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{5t'} W_{t't}}^{\text{Week Effect}} \\
& + \overbrace{\sum_{m \in \mathbb{M}} \delta_{6m} M_{jmti}}^{\text{Marketing Mix Effect}} + \overbrace{\sum_{z \in \mathbb{U}} \delta_{7z} \Big(D_{jti} Z_{jz} \Big)}^{\text{Display-SKU Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{8t'} \Big(D_{jti} W_{t't} \Big)}^{\text{Display-Week Effect}} + \\
& + \overbrace{\sum_{a=1}^{C} \sum_{t'=1}^{T} \delta_{9at'} \Big(A_{ja} W_{t't} \Big)}^{\text{Subcategory-Week Effect}} \overbrace{\sum_{m \in \mathbb{M}} \sum_{g \in \mathbb{G}} \delta_{10gm} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} M_{j'mti} (1 - M_{jmti})}^{\text{Cross-Marketing Mix Effects}} \\
& + \overbrace{\sum_{g \in \mathbb{G}} \delta_{11g} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} D_{j'ti} (1 - D_{jti})}^{\text{Cross-Display Effect}} \\
& + \overbrace{\sum_{i'=1}^{I} \delta_{12i'} B_{i'i}}^{\text{Store Effect}} + \overbrace{e_{jti}}^{\text{Error Term}}
\end{aligned} \tag{1.1}
$$

Since the majority of grocery store purchases are done in smaller quantities, we log-transform the dependent variable (i.e., sales of SKU j at store i in week t) to mitigate the positively skewed distribution of sales in our dataset. Marketing mix instruments can be time-dependent [Mela et al., 1997] and vary by product [Blattberg et al., 1995]. Thus, we capture the total display effect through the main display effect and two related interaction terms Display-Week and Display-SKU. Our model includes weekly indicators that not only account for seasonality in the consumption of the product [Fok et al., 2007] but also for potentially unobserved weekly effects such as manufacturer advertising. It also includes SKU indicators. (Specifically, Z_{jz}

IRI and Nielson), specifically, at the store/week/SKU level, and there are hundreds or even thousands of various SKUs available at the time for purchase.

is a vector of distinct SKUs in the consideration set for promotional display, in which one element represents all "other" SKUs not included in the consideration set). The model also accounts for subcategory seasonality by including the interaction term Subcategory-Week[11]. We control for the SKU's price both directly and indirectly through its percentage discount, also referred by Nijs et al. [2001] and Raju [1992] as "promotional depth"[12]. We also include store dummies to control for store-specific fixed effects. These store-specific fixed effects are critical to our model, as they eliminate bias that might otherwise occur from factors such as store size and unobservable manager skills that could affect both store sales and promotional display decisions.

In addition to a SKU's own-marketing mix effects, our model, consistent with the prior literature [Rooderkerk et al., 2013], also accounts for cross-marketing mix-effects, where the cross-effects are moderated by the degree of similarity between SKUs. This is in line with the assertion that promoted items through some marketing mix activities will have a stronger effect (either positive or negative) on similar versus dissimilar (non-promoted) items [Rooderkerk et al., 2011, Tversky, 1972]. Thus, we need a metric to capture such similarity. We build on the prior literature [Hardie et al., 1998, Rooderkerk et al., 2013] and adopt an attribute-based similarity metric/variable. The similarity variable ($SIM_{jj'gti}$) explicitly accounts for the fraction of SKUs that share the same attribute during each store-week pair. More precisely, the proposed metric possesses an important characteristic: "the similarity between two SKUs on a given attribute should not only reflect the similarity of their own attribute levels, in an absolute sense but also vis-à-vis the full distribution of attribute levels in the assortment. In particular, if two items share the same level of a nominal attribute (e.g., package type), their perceived similarity should be stronger when their shared

[11] We consider subcategory seasonality as opposed to SKU seasonality as it reduces the number of interactions that have to be estimated and prevents overfitting.

[12] An interaction term between display and price reduction turned out to be insignificant and thus is not included.

attribute level occurs less frequently" [Rooderkerk et al., 2013, p.703]. The definition of this similarity variable is given in (1.2)[13].

$$SIM_{jj'gti} = I\{A_{jg} = A_{j'g}\} \times \left(1 - \frac{\sum_{j''=1}^{J} I(A_{j''g} = A_{jg})}{N_{ti}}\right), \tag{1.2}$$

where $I\{A_{jg} = A_{j'g}\}$ indicates if the arguments hold true (1), or not (0); A_{jg} is the level attained by a SKU on attribute g such that $A_{jg} = m \Leftrightarrow A_{jgm} = 1$; N_{ti} is the number of SKUs present in week t in store i. Thus, for every attribute of a product, we construct a similarity variable that accounts for the distribution of attribute levels at the store/week level. The similarity values for the observations that do not belong to a specific attribute are zero, thus $SIM_{jj'gti}$ varies between 0 (no similarity) and 1 (identical).

We next provide a simple illustration of how $SIM_{jj'gti}$ is constructed. Consider that we are interested in selecting SKUs for promotional display from the beer category and an important attribute g is the calorie content, which classifies beer SKUs as light versus regular. If at a single store/week level, 1 out of 4 beer SKUs is light, then the similarity of one light beer SKU to another light beer SKU (expression within the parenthesis in (1.2)) is $1 - 0.25 = 0.75$. Likewise, for the remaining 3 regular beer SKUs, the similarity of any pair of these beer SKUs is $1 - 0.75 = 0.25$.

One modification to the methodology proposed by Rooderkerk et al. [2013] is that we recognize that it makes little sense to obtain the substitution effect of SKU j on

[13]Please note that an alternative definition of similarity was considered where the similarity of attribute levels among SKUs was also tested in a binary sense, i.e., without considering the full distribution of attribute levels in the assortment. In this case, attributes are classified as 1 (similar) or as 0 (dissimilar). However, the statistical fit is better with the former definition given in equation (1.2). Additionally, since Ma and Fildes [2017] employed LASSO to reduce the number of cross-effects, we also tried using LASSO with cross-effects in lieu of similarities. In general, our similarity metrics are less computationally burdensome than the cross-effects and yield similar results.

SKU j' or of SKU j' on SKU j when both products are on display, in the same week, since this approach reduces the main display effect. Thus, unlike Rooderkerk et al. [2013], when a pair of SKU j and SKU j' are placed together on promotional display, we incorporate the terms $(1 - D_{jti})$ and $(1 - M_{jmti})$ into their respective similarities to keep the main display effect "undisturbed". As a result, when $SIM_{jj'gti}D_{j'ti}$ is multiplied by $(1 - D_{jti})$, when both SKU j and SKU j' are on promotional display, and when $SIM_{jj'gti}M_{j'mti}$ is multiplied by $(1 - M_{jmti})$, when both SKU j and SKU j' are on a marketing mix promotion, the overall similarity effect will be zero because $D_{j'ti} = M_{j'mti} = 1$ and $(1 - D_{jti}) = (1 - M_{jmti}) = 0$. Thus, in our estimation model (1.1), the terms $\sum_{m \in \mathbb{M}} \sum_{g \in \mathbb{G}} \delta_{9gm} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti}M_{j'mti}(1 - M_{jmti})$ and $\sum_{g \in \mathbb{G}} \delta_{10g} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti}D_{j'ti}(1 - D_{jti})$ measure the cross-promotional (including feature, price reduction, display) responsiveness across SKUs moderated by their attribute-based similarity. A summary of our notation is provided in Table 1.2 and 1.3. We elaborate on our model fit in Section 1.5 and present the rationale of our model development in Appendix 3.5.

After estimating our model on a large dataset that includes many different stores and many different grocery chains, we next apply these estimated coefficients to the data from each store i to calculate the incremental profit Π_{jti} i.e., the additional profit obtained from placing each potential SKU j on display at store i in week t. After choosing the SKUs for promotional display for each week in the planning horizon, this procedure can be repeated for all stores.

1.3.2 Calculation of Total Incremental Profit

The total incremental profit (Π_{jti}) from placing a particular SKU on display is the sum of the incremental profit from its own sales ("own-display profit") and the incremental profit from the sales of other SKUs within the pre-selected category ("cross-display profit"). The own-display profit is the product of SKU j's own base demand q_{jti}, its

Table 1.2: Description of Variables and Symbols

Variable	Description
$\ln S_{jti}$	log unit sales of SKU j for $j = 1, 2, \ldots, J$ in store i for $i = 1, 2, \ldots, I$ in week t for $t = 1, 2..., T$
A_{ja}	indicator variable, $= 1$ when SKU j is part of subcategory V_a
D_{jti}	indicator variable, $= 1$ when SKU j at store i in week t is put on display; 0 otherwise
$W_{t't}$	indicator variable, $= 1$ if $t = t'$; 0 otherwise
M_{jmti}	indicator variable, $= 1$ when marketing mix instrument $m \in \mathbb{M}$ is applied to SKU j at store i in week t
H_{jti}	size of price reduction in cents for SKU j at store i in week t
Z_{jz}	indicator variable for SKUs, $= 1$ if j equals SKU z; 0 otherwise (one "dummy" represents all "other" SKUs not included in the consideration set)
$B_{i'i}$	indicator variable, $= 1$ if $i = i'$; 0 otherwise
$SIM_{jj'gti}$	similarity of SKU j to SKU j' for an attribute g in week t and store i

display lift, l_{jti}, and its profit margin, π_{jti}. The cross-display profit for a SKU j' that results from SKU j being on display is the product of SKU j''s base demand, $q_{j'ti}$, the cross-display lift, $CEL_{jj'i}$ of SKU j' from putting SKU j on display, and product j''s profit margin, $\pi_{j'ti}$. $\triangle$ is a smearing correction factor, which offsets errors associated with the exponential re-transformation of predicted estimates [Duan, 1983].

$$\Pi_{jti} = \overbrace{q_{jti}(l_{jti} - 1)\pi_{jti}\triangle}^{\text{Own-display profit}} + \overbrace{\sum_{j' \neq j} q_{j'ti}(CEL_{jj'i} - 1)\pi_{j'ti}\triangle}^{\text{Cross-display profit}} \tag{1.3}$$

We next show how to construct each factor of the total incremental profit in (1.3)[14].

Own-display profit $\boldsymbol{q_{jti}(l_{jti} - 1)\pi_{jti}\triangle}$: These calculations use the estimated parameters (i.e., $\hat{\delta}$s) from the SKU-level sales response function (1.1). The base demand q_{jti} (1.4) is calculated by subtracting from the log-transformed unit sales the estimated effects related to own- and cross-marketing related activities such as

[14] A trade allowance associated with store i, SKU j in week t can easily be added to this profit function as an additive term.

Table 1.3: Description of Variables and Symbols

Symbol	Description
x_{jt}	binary decision variable which equals to 1 if SKU j is placed on display in week t, 0 otherwise
Π_{jti}	the incremental profit obtained from placing SKU j on display at store i
b_j	in week t the maximum number of times a SKU j can be promotionally displayed across the time horizon.
k_t	the maximum number of displays available in week t
c_{jt}	a binary indicator, equals to 1 if SKU j goes from being on display to being off display in week t
q_{jti}	the base demand for SKU j in week t at store i
l_{jti}	the display lift for SKU j in week t at store i
π_{jti}	the profit margin of SKU j sold in week t at store i
o_{jti}	a manufacturer-sponsored trade promotion for SKU j sold in week t at store i
g	a product attribute (i.e., package size, calorie content, brand, container type)
$\mathbb{U}$	a set of SKU candidates evaluated to be placed on a promotional display with the proposed approach
$\mathbb{V}$	a set of SKU candidates evaluated to be placed on a promotional display with the Hierarchical approach (Appendix 3.5)
C	the number of subcategories
$\mathbb{V}_a$	a disjoint union partitioning $\mathbb{V}$ into C subcategories; $\mathbb{V} = \mathbb{V}_1 \cup \mathbb{V}_2 \cup \cdots \cup \mathbb{V}_C$
$\mathbb{D}_{ti}$	the set of displays available at week t at store i
$\mathbb{M}$	the set of all marketing mix instruments including temporary price reduction, coupon, feature, and advertisement excluding promotional display
T	the number of weeks of history used in the estimation
$\tilde{T}$	the number of weeks to optimize for in the (dynamic) optimization
Q_j	a consecutive set of weeks
R	the cost the retailer incurs every time a product on display is replaced
G	a full set of product attributes
$CEL_{jj'i}$	a cross-display lift of SKU j' from putting SKU j on display
J	all available products
$\triangle$	smearing correction factor

promotional display, feature advertising, and price reduction. In other words, it represents the unit sales of SKU j in the absence of any external influences of price reduction, feature advertising, and promotional display, as well as any marketing-mix-related cross-effects.

$$\begin{aligned}\ln\left(q_{jti}\right) &= \ln S_{jti} - \hat{\delta}_2 D_{jti} - \hat{\delta}_3 H_{jti} - \sum_{m\in\mathbb{M}} \hat{\delta}_{6m} M_{jmti} - \sum_{z\in\mathbb{U}} \hat{\delta}_{7z}\left(D_{jti} Z_{jz}\right) \quad (1.4)\\ &- \sum_{t'=1}^{T} \hat{\delta}_{8t'}\left(D_{jti} W_{t't}\right) \sum_{m\in\mathbb{M}} \sum_{g\in\mathbb{G}} - \sum_{j'=1/\{j\}}^{J} \hat{\delta}_{10gm} SIM_{jj'ti} M_{j'mti}(1 - M_{jmti})\\ &- \sum_{g\in\mathbb{G}} \sum_{j'=1/\{j\}}^{J} \hat{\delta}_{11g} SIM_{jj'ti} D_{j'ti}(1 - D_{jti}) \quad (1.5)\end{aligned}$$

The SKU-level display lift l_{jti} (1.6) is also obtained by using the estimates from (1.1), where we sum up the main and all partial display effects:

$$\ln\left(l_{jti}\right) = \hat{\delta}_2 D_{jti} + \sum_{z\in\mathbb{U}} \hat{\delta}_{7z}\left(D_{jti} Z_{jz}\right) + \sum_{t'=1}^{T} \hat{\delta}_{8t'}\left(D_{jti} W_{t't}\right) \quad (1.6)$$

Since we log-transform l_{jti} in (1.6), we have $l_{jti} = 1$ when $D_{jti} = 0$. Thus, the actual display lift associated with placing SKU j on promotional display in week t at store i is $l_{jti} - 1$.

Cross-display profit $\sum_{j'\neq j} q_{j'ti}(CEL_{jj'i} - 1)\pi_{j'ti}\triangle$: The cross-display profit is captured through the attribute-based, cross-display effect among products $CEL_{jj'i}$ calculated in (1.7), which captures the effect of placing SKU j on promotional display to the demand of other SKUs j' moderated by the degree of similarity between the SKUs:

$$\ln(CEL_{jj'i}) = \sum_{g\in\mathbb{G}} \hat{\delta}_{11g} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} D_{j'ti}(1 - D_{jti}), \quad (1.7)$$

where the summation over G is performed over all nominal attributes g. Here, the collection of individual $CEL_{jj'i}$ is represented by a square matrix, where each vertical column of values indicates a multiplier effect (less, greater, or equal to one) on each SKU j' in the store's (product) category assortment resulting from putting another SKU j on display, assuming the rest of the SKUs are also present in that assortment. The values are store-specific but time-invariant because, for optimization purposes, we assume the store's assortment stays constant over the planning horizon. For example, if the effect of displaying SKU j on SKU j' results in a multiplier effect of 1.01, we expect a 1% increase in the cross-display profit of SKU j'. Alternatively, if the multiplier effect were 0.99, we expect a 1% decrease in the cross-display profit of SKU j'. We let the multiplier effect of a SKU on itself have no cross-display effect, i.e., the diagonal values of the matrix equal to 1. Note that $q_{j'ti}$ is the pairwise base demand of another SKU, and $\pi_{j'ti}$ is the pairwise profit margin of that SKU. The sum of all individual cross-display profits is the total cross-display profit obtained across the entire category assortment when SKU j is on display and the other SKUs are not[15].

1.3.3 Static Optimization

We next develop a static optimization model that a retailer can use to identify the profit-maximizing SKUs to place on promotional display for each week in the planning horizon. The optimization model can be run independently for every store i in every week t. For this reason, we drop the subscripts i and t. The objective function of the optimization model takes Π_{jti} (or Π_j) as an input (see (1.3)). It can also account for any trade promotion allowance o_{jti} (or o_j) offered by a manufacturer to the retailer for placing SKU j on promotional display at week t in store i:

$$
\begin{aligned}
\max_{x_{jd}} \quad & \textstyle\sum_{j\in\mathbb{U},d\in\mathbb{D}}(\Pi_j + o_j)x_{jd} \\
\text{subject to} \quad & \textstyle\sum_{j\in\mathbb{U}} x_{jd} \leq 1,\ \forall d \in \mathbb{D}, \\
& \textstyle\sum_{d\in\mathbb{D}} x_{jd} \leq 1,\ \forall j \in \mathbb{U}, \\
& x_{jd} \in \{0,1\}.
\end{aligned}
\tag{1.8}
$$

Here, the binary decision variable x_{jd} is 1 if SKU j can be placed on display d (at store i in week t), and we only have such decision variables for those combinations

[15]In Appendix 3.5 we discuss how to add cross-display effects from other product categories.

of SKU j and display d where SKU j is a legitimate candidate for display d. For example, some displays may be freezers, and thus only SKUs requiring refrigeration will be candidates. Other displays may have restrictions on the size of items that may be displayed on them. In addition, the retailer may desire certain SKUs to always be displayed next to particular merchandise, or certain SKUs not to be displayed too close to the entrance for security reasons. Such business rules can be easily incorporated into the optimization model.

We now discuss the constraints that we impose. The first constraint states that each display d can have at most one SKU on it[16], while the second constraint states that each SKU can be on at most one display. Thus, this problem becomes a variation of the maximum weighted bipartite matching problem, where the left-hand nodes are SKUs and the right-hand nodes are displays and the weight of an edge between SKU j and display d is the incremental profit $\Pi_j + o_j$. The bipartite graph only contains an edge between SKU j and display d if SKU j is allowed to be on display d (i.e., if the decision variable x_{jd} is present in the above objective function). The solution to the above problem involves simply rank ordering all the SKU candidates (for every store i in every week t) based on their incremental profit and choosing the top $|\mathbb{D}|$ SKUs to be placed on promotional display, where $|\mathbb{D}|$ denotes the number of available displays. We resolve the problem every week on a rolling horizon basis.

1.3.4 Dynamic Optimization

In this section, we describe a dynamic version of the promotional display optimization problem to determine the SKUs to be assigned to promotional display in a single optimization run over every week in the planning horizon. Our optimization problem

[16] Our methodology can be easily extended to cases where more than one SKU can be located on the same promotional display space.

can be solved on a rolling horizon schedule and our model is flexible enough to incorporate as constraints some important business rules typically applied in practice.

Some retailers may want to impose a limit on how frequently a particular product can appear on display. For example, knowing that frequent promotion is likely to lose some effectiveness over time, a grocer may want to impose the constraint that certain SKUs may appear on display at most twice in a month. In addition, some retailers may have some general business rules that store managers must follow, such as requiring that no single subcategory can be on display for more than two consecutive weeks. To include a greater product diversity on promotional display across time, we define a new objective function (1.9) and constraints (1.10) – (1.13). The constraints that we consider in the dynamic optimization are typical constraints that are often used in the promotions/pricing literature (e.g., Elmaghraby and Keskinocak [2003]) and the shelf space[17]/assortment optimization literature (e.g., **?**Gallego and Topaloglu [2014]) to address realistic issues faced by retailers. We illustrate how these types of constraints can be adopted in a new setting to address specific issues pertinent to the promotional display optimization based on our conversations with store managers. The optimization is done independently for each store, hence, the subscript i is dropped. (Unlike the static optimization, we don't drop the subscript t, since the decisions are no longer independent across time.)

$$\max_{x_{jt}} \quad \sum_{j\in\mathbb{U}} \sum_{t=1}^{\tilde{T}} (\Pi_{jt} x_{jt} - R \times c_{jt}) \tag{1.9}$$

subject to

$$\sum_{j\in\mathbb{U}} x_{jt} \leq k_t, \ \forall t < \tilde{T} \tag{1.10}$$

[17]This family of constraints is identified in the shelf space optimization literature as control or capacity constraints, where retailers set lower and/or upper bounds for products' days-supply, brand share, and shelf-space exposure, used to manage operational costs associated with stock-outs and replenishments.

$$\sum_{t=1}^{\tilde{T}} x_{jt} \leq b_j, \ \forall j \in \mathbb{U} \tag{1.11}$$

$$\sum_{r=0}^{Q_j} x_{j,t+r} \leq 1, \ \forall j, \ \forall t \tag{1.12}$$

$$x_{jt} - x_{j,t+1} \leq c_{jt}, \ \forall j, \ \forall t \tag{1.13}$$

$$x_{jt} \in \{0,1\}, \ c_{jt} \in \{0,1\} \tag{1.14}$$

Objective function. The objective function (1.9) defines the profitability of a promotional display decision over the entire time horizon $\tilde{T}$. The first term in the summation is the total incremental profit obtained from placing SKUs on promotional display in week t. The second term is the total changeover cost associated with changing a display. Updating a promotional display might be costly as removing one product and replacing it with another requires additional labor hours. Specifically, we assume that every time a SKU j has to be removed from the display, the retailer incurs some cost R. To capture the incremental profitability and the display-related changeover cost, we define x_{jt} as a binary decision variable which equals to 1 if SKU j is placed on display in week t, 0 otherwise; and c_{jt} as a binary indicator, which equals to 1 if SKU j goes from being on display to being off display in week t.

Display-Space Restriction. Constraint (1.10) indicates the total number of displays available per week, where k_t is the maximum number of promotional displays available in week t (referred in operations literature as a capacity or space constraint [Rusmevichientong et al., 2010, Gallego and Topaloglu, 2014]).

Week Restriction. Constraint (1.11) indicates that a SKU j can be promotionally displayed at most b_j number of times across the time horizon.

Sparsity Restriction. Constraint (1.12) requires that in every Q_j consecutive set of weeks, SKU j can only be promotionally displayed once (also referred in operations literature as a cardinality constraint [Gallego and Topaloglu, 2014]). This way, a decision-maker can impose a limitation on the successive frequency of promotional activity over time [Elmaghraby and Keskinocak, 2003]. In other words, a retailer can indicate how many weeks *in a row* a product can be displayed.[18]

Changeover Cost. Constraint (1.13) is needed to indicate a changeover, which occurs every time a SKU has to be removed from display. Here, the value of x_{jt} determines the value of c_{jt}. Table 1.4 illustrates how the binary "change detector" c_{jt} obtains its value once x_{jt} is known. The profit-maximizing objective function will always force c_{jt} equal to 0 in the first three cases. In the last case, c_{jt} is forced to equal 1, hence, a changeover cost is incurred.

Table 1.4: How c_{jt} obtains its value from $x_{jt} - x_{j,t+1} \leq c_{jt}$

x_{jt}	$x_{j,t+1}$	$x_{j,t} - x_{j,t+1}$	Interpretation	c_{jt}
0	1	-1	SKU j went from not being on display to being on display	0
0	0	0	SKU j was not and is not on display	0
1	1	0	SKU j remains on display this week too	0
1	0	1	SKU j went from being on display to not being on display	1

In large retail stores that offer a wide selection of SKUs within different product categories the number of possible SKUs to be considered as candidates for promotional display could be very large which can increase substantially the computational time of the optimization model. To address this, we propose an approach that we call pre-processing which limits the number of SKUs to be evaluated in the optimization model while still guaranteeing optimality. We discuss the specifics of this approach in Appendix 3.5. Having described our methodology in this section, we next describe a publicly available dataset of grocery store transaction data that we use to demonstrate our methodology.

[18]Alternatively, one can consider a non-sparsity constraint. In this case, a retailer can indicate how many consecutive number of weeks a product should not be displayed.

1.4 Data Description

1.4.1 Estimation data (all stores)

For parameter estimation, we use a sample of syndicated retail sales scanner data collected by IRI, known as the IRI Marketing Data Set [Bronnenberg et al., 2008]. Unlike a retailer's proprietary data that is limited to the sales of one particular retailer, syndicated data comes from a variety of retail sources and is gathered by a third party (e.g. IRI or Nielsen). Syndicated data represents a richer source of information because it covers more than one retailer, thus, containing information on more products across more markets and numerous grocery store chains. The initial dataset covers more than 1,200 stores across 50 US markets. We illustrate our methodology using a sample from the New England region, which covers a variety of retail outlets with more than 102 stores in total. Focusing on the New England region reduces differences in beer demand/consumption due to differences in customer preferences across geographic locations and weather conditions. The dataset covers five US markets in the New England Region such as 'Boston', 'Hartford', 'Pittsfield', 'Providence', and 'Other New England'[19] for all fifty-two weeks of the latest available year, 2011, and is structured at a SKU/store/week level, with a total of 387,228 sales observations.

We focus on the sales of beer/malt beverages since this product category is typically one of the most popular impulse buy purchases, and is thus a popular choice for promotional display spaces [Bell et al., 2009]. Although agreement over the proper segmentation framework does not always exist [Hausman et al., 1994], we follow Kok and Fisher's (2007) definition of a subcategory, and classify SKUs based on product quality such that the difference between products within a subcategory is minimal but the difference across subcategories is significant (Ibid, p. 1001). By using pub-

[19]Other New England markets besides Boston, Hartford, Pittsfield, and Providence.

licly available data on beer/malt beverage types from the Department of Alcoholic Beverage Control, beeradvocate.com and proprietary data from the Craft Brewers Association, we classify the available SKUs into mass-produced beers like Subpremium, Premium, Super Premium, and more niche beers like Craft and Import. Due to a wide variety of package sizes sold (from single bottles to 36-can packs), we only consider the most popular package sizes: 6-, 12-, 18-, and 24-unit products[20]. We exclude unusually expensive transactions with a unit cost greater than $1 per ounce (e.g., Samuel Adams' Utopia at $150 per 24 oz. bottle). Additionally, we exclude oddly shaped and rarely purchased product packages like party balls and kegs, since our focus is on endcap displays and these package types are often put on floor displays. A summary of our dataset is provided in Table 1.5.

Table 1.5: New England Data Set Summary

Subcategory	**Observations**	**Unit sales**	**SKU count**	**SKU count on display**
Subpremium	35,653	149,554	59	10
Premium	80,699	720,379	75	45
Superpremium	70,830	332,791	85	44
Craft	116,008	632,439	352	105
Import	84,038	432,586	159	60
Total	**387,228**	**2,267,749**	**730**	**264**

The top-selling subcategories by volume are Premium (720,379 units sold), Craft (632,439 units sold), Import (432,586 units sold), Superpremium (332,791 units sold), and Subpremium (149,554 units sold). Craft has the most diverse set of products with a total of 352 SKUs, followed by Import (159 SKUs). The top-selling Premium subcategory has only 75 distinct SKUs.

[20]Our main results continue to hold when we include the full set of package types.

Each observation in our dataset includes detailed information on the following: the SKU that was sold, the number of units sold, the total number of dollars paid, the week of purchase, whether there was any marketing mix activity associated with the transaction (i.e., whether the SKU was on promotional display, whether there was any price reduction, whether it was featured in a store flyer or advertised in other ways), various SKU characteristics, the geographic region of the store, and the store's unique identifier. Table 1.6 provides overall information on transactions with promotional display activity. An example of a typical transaction is 21 units of SKU 00-01-18200-00016 (Budweiser, can, 6-pack) sold for $125.79 in week 16 at store #250872, with no promotional activity associated with this transaction (i.e., no price promotion, no promotional display, and no coverage in any store flyers).

Table 1.6: Categorization of Sales Transactions

Promotional display	**Units Sold**	**Frequency of Observations**
No	2,120,514	372,508
Yes	147,235	14,720
Total	2,443,753	387,228

All beer SKUs are uniquely identified using four nominal attributes: calorie content (light, regular), container type (bottle, can), package size (6-, 12-, 18-, 24-pack), and brand (thirty-three brands in total). Thus, our similarity variables are created for all attributes of beer SKUs at the store/week level as discussed in Section 1.3.1. Table 1.7 provides descriptive statistics of the dataset for select variables that we include in our estimation model. It is clear from Table 1.7 that price reduction is the most frequent type of promotional activity in the beer category while the promotional display is the least frequent type of promotional activity, possibly because promotional displays are constrained by the capacity of available endcaps.

Table 1.7: Descriptive Statistics for Select Variables (All Stores)

Variable	Obs	Mean	Median	Min	Max
Unit Sales	387,228	5.61	3	1	570
Display (Binary)	387,228	3.60%	0	0	100%
Price per bottle/can (dollars)	387,228	1.10	1.08	0.12	2.99
Discount Percentage	387,228	5.60%	4%	0	77%
Price Reduction (Binary)	387,228	18.70%	0	0	100%
Feature (Binary)	387,228	8.40%	0	0	100%

1.4.2 Optimization data (single store)

We illustrate the selection of the optimal SKUs to be placed on promotional display for a randomly chosen store i located in New England. Overall, 334 SKUs in the five subcategories were sold at this store over the entire year (see Table 1.8). Note that only 12 of these 334 SKUs were selected for promotional display, reinforcing our earlier point that a single store lacks the data needed to estimate the promotional display lift for most SKUs. The top-selling subcategories by volume are Premium (53,999 units), Craft (21,601 units), Superpremium (21,233 units), Import (19,336 units), and Subpremium (6,110 units)[21].

1.5 Application and Assessment of Methodology

In this section, we demonstrate our methodology, assess its performance, and evaluate its expected improvement in incremental store profits compared to some common benchmark heuristics used in practice. Our goal is to select the profit-optimizing SKUs to place on promotional display at a randomly selected store and compare the performance of our proposed methodology against the performance of a commonly used practice in the grocery industry.

[21]*Out of 12 SKUs, 8 were displayed only once and 4 were displayed four times each.

Table 1.8: Single Store Sales Data Summary

Subcategory	**Observations**	**Unit sales**	**SKU count**	**SKU count on display**
Subpremium	1,050	6,110	27	0
Premium	2,007	53,999	50	12*
Superpremium	1,947	21,233	47	0
Craft	3,392	21,601	102	0
Import	2,637	19,336	67	0
Total	**12,529**	**129,530**	**334**	**12**

1.5.1 SKU short-listing

We next describe how we short-list the beer SKUs to consider as potential candidates for promotional display. Since it is unlikely that a very low selling SKU will be selected, we impose a lower bound on the number of units sold as an important selection criterion. Another important selection criterion is the frequency of a SKU's display activity relative to the other SKUs in the overall sample (used for estimation purposes). To accurately measure the sales lift associated with placing a SKU on promotional display, that SKU should also have a minimal reasonable frequency of display. Thus, we short-list the SKUs to be evaluated in our estimation and optimization models if the following two criteria are met: i) sold units of a SKU were displayed for at least 3% of the entire SKU-week level data, and ii) at least 5000 units have been sold in the entire year. This results in a set of 59 potential SKUs to be included in our consideration set (see Appendix 3.5 for a full list of these SKUs).

Table 1.9: Sales Response Function Estimates

	Model
ln(Unit sales)	
Constant	0.6923***
	(0.0572)
Price	-0.0003
	(0.0005)
Discount percentage	1.4700***
	(0.1251)
M_{jmti}	
Price Reduction (binary)	-0.0510***
	(0.021)
Feature	0.1923***
	(0.0344)
D_{jti}	
Display (binary)	0.235***
	(0.0876)
Display-SKU	Included
Display-Week	Included

1.5.2 Estimation

Tables 1.9 and 1.10[22] summarize the regression results for the model obtained using the sales response function (1.1), which is estimated for all candidate SKUs listed in Appendix 3.5. Our statistical inference is based on cluster-robust standard errors so our estimates are robust to both arbitrary heteroscedasticity and arbitrary intra-store correlation. Our key variable of interest is display (and its interaction terms display-SKU and display-week) controlling for price and different marketing-related activities (i.e., discounts, temporary price reductions, advertisements, coupons). We

[22]Additional controls are included such as week dummies, SKU dummies, store dummies, and the interaction term between subcategory and week. Robust standard errors clustered at the store level are in parenthesis.

Table 1.10: Sales Response Function Estimates (cont.)

	Model
ln(Unit sales)	
$SIM_{jj'gti}M_{j'mti}(1 - M_{jmti})$	
Calorie Content (Price Reduction)	-0.0066***
	(0.0022)
Container Type (Price Reduction)	-0.0175***
	(0.0031)
Package Size (Price Reduction)	0.0021
	(0.0014)
Brand (Price Reduction)	0.0909***
	(0.0087)
Calorie Content (Feature)	-0.0023
	(0.0087)
Container Type (Feature)	-0.0030***
	(0.0021)
Package Size (Feature)	-0.0110***
	(0.0032)
Brand (Feature)	0.0800
	(0.0012)
$SIM_{jj'gti}D_{j'ti}(1 - D_{jti})$	
Calorie Content (Display)	-0.0010
	(0.0049)
Container Type (Display)	0.0019
	(0.0053)
Package Size (Display)	-0.0131***
	(0.0034)
Brand (Display)	0.1162***
	(0.0192)
Additional controls	Included
AIC	682829.5
BIC	683535.8
Obs.	387,228

also include additional controls such as week dummies, SKU dummies, store dummies, the interaction term between subcategory and week and cross-SKU promotional (i.e., price reduction, feature advertising, and promotional display) variables moderated by the similarities between SKUs.

The main effect of display is significant in magnitude i.e., providing an average 27% lift in weekly sales. The interaction terms display-SKU and display-week are mostly significant. (The estimates of those interaction effects are not reported in the table due to space considerations). The size of discount and feature advertising also have a positive and statistically significant impact on sales as expected. The similarity-based moderation of cross-promotional responsiveness is statistically significant across most attributes and promotional instruments, but it varies in magnitude and sign. For instance, the interactions between brand-similarity and cross-marketing mix instruments are positive across all promotional instruments suggesting that a promoted brand can have a positive halo effect on non-promoted products of the same brand [Leuthesser et al., 1995]. On the other hand, the interactions between other attribute-based similarities (i.e., calorie content, package size, and container type) and cross-marketing mix instruments are mainly negative and small in magnitude suggesting that SKU sales are moderately cannibalized by similar (in terms of calorie content, package size, container type) SKUs that are promoted [van Heerde et al., 2004].

1.5.3 Assessment of our Estimation Methodology

To test against overfitting, we evaluate the out-of-sample performance of our estimation model. Since we only have one year of data, we split our dataset at the store level into two datasets, an estimation sample and a test sample (70% estimation and 30% test). Out of 102 stores in total, 71 stores are randomly selected for the estimation sample with the remaining 31 stores selected for the test sample. We used the estimation sample to estimate the model coefficients and then used the estimated model to predict the sales for the test sample. Three popular forecasting metrics were used to evaluate the performance of our estimation model i.e., mean absolute percentage error (MAPE), symmetric mean absolute percentage error (sMAPE[23]), and median absolute percentage error (MdAPE). The in-sample MAPE was 37.5% and the out-of-sample MAPE was 43% while the in-sample sMAPE was 31.6% and the out-of-sample was 33.30%. With regards to the third forecasting metric, the in-sample MdAPE was 15% and the out-of-sample was 18%. The similarities between the in-sample and out-of-sample performance with all three metrics indicate little evidence of overfitting. As far as the magnitude of the forecasting error is concerned, discussions with one of our industry partners confirmed that this is solid in-sample and out-of-sample performance given the fact that forecasting is performed at this level of granularity (i.e., SKU/week/store level).

We also test our original modelâĂŹs predictive power on sales data from a single chain in New England. Out of the seven chains present in the dataset, we chose the chain with the largest number of stores - thirteen. Since data from a single chain, by nature, is more homogenous than data from multiple chains, we expected that the predictive power of the regression model would improve. The results were an in-sample MAPE of 34.12% versus an out-of-sample of 35.77%, an in-sample sMAPE of 29.10% versus an out-of-sample of 30.50% and an in-sample MdAPE of 14.48% versus an out-of-sample of 14.58%. As expected, the predictive power of the model improves when the dataset is more homogenous i.e., belongs to one chain.

[23]sMAPE is a modified MAPE in which the divisor is half of the sum of the actual and forecast values and deals with certain limitations of the MAPE (for more detail, see Makridakis [1993]).

1.5.4 Application of the Static Optimization

To calculate the total incremental profit for every candidate SKU j in week t for store i as shown in (1.3), we feed the estimates of (1.1) into (1.4), (1.6) and (1.7). Since we don't have access to actual product profit margins, we set a profit margin equal to 25% of each SKU's full price, which is consistent with the measurement of profit margin in prior retail operations work [Dreze et al., 1994, Campo et al., 2004, Rooderkerk et al., 2013]. For this application, the cross-display profit in (1.3) is, as mentioned earlier, store-specific and time-invariant.

Our optimization suggests that the beer SKU Bud Light (bottle, 18-pack) provides the highest incremental profit in almost every week (see Figure 2 in Appendix 3.5) except for several weeks in the middle and end of the year where the profit-maximizing SKU is Budweiser (bottle, 24-pack). The total incremental profit (across all weeks) obtained by the proposed approach is $16,425.

Table 1.11 provides statistics regarding the estimated total incremental profit, broken down between the incremental profits of the own-display and the cross-display effects of each SKU selected to be placed on promotional display over a horizon of 52 weeks. Note that the product of the average base demand (94.61 units), average total display lift (71%), average profit per unit sold ($3.20), and the smearing correction (1.33) results in $285.88, which is the estimated average own-display incremental profit. The estimated average cross-display profit is $29.96, which is much smaller in magnitude than the estimated average own-display incremental profit as expected. The average total incremental profit turns out to be approximately $316.

1.5.5 Static Benchmark Comparison

We now examine how the profits obtained using our methodology compare with the profitability of a commonly used practice by retailers. A standard and commonly used approach to choose a product for promotional display, which will serve as our

Table 1.11: Statistics for Total Incremental Profit, Own-Display Incremental Profit, and Cross-Display Incremental Profit of the Selected SKUs; with Smearing Correction Δ=1.33

	Obs.	Mean	Median	Min	Max
Base Demand	52	94.61	86.02	39.25	198.29
Total Display Lift	52	71%	69%	45%	102%
Profit Per Unit Sold (25% of original price, dollars)	52	320	2.99	299.75	374.75
Own-Display Incremental Profit (dollars)	52	285.88	269.20	111.54	644.92
Cross-Display Incremental Profit (dollars)	52	29.96	10.52	-67.75	26.11
Total Incremental Profit (dollars)	52	315.74	291.23	120.69	688.34

benchmark, is to pick a best-selling SKU in that week. In reality, store managers do not know in advance which SKU will be the best-seller for the incoming week and need to rely on forecasts. Since we only have one year of data, we assume that store-managers have full information regarding which SKU will be best-selling for the incoming week. Thus, we construct our benchmark by first observing what the best-selling SKU is in each week, assigning that SKU on promotional display and then calculating the corresponding incremental profit associated with that placement. Hence, using this benchmark represents a conservative comparison (relative to our heuristic) because it assumes that the store manager has a perfect forecast. The set of SKUs that are assigned on a promotional display based on this commonly used approach is summarized in Table 1.12 and depicted in Figure 3 in Appendix 3.5. The benchmark yields an annual incremental profit of $8,255. It is interesting to note that even though we assume the store-manager has full information while constructing our benchmark, we find that the proposed approach outperforms the benchmark.

Table 1.12: SKUs Chosen in Benchmark

Top SKU	**Annual unit sales**	**Top seller in week**
Bud Light, bott., 18-pack	5,822	0, 16, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 34, 3537, 40, 41, 48
Bud Light, can, 18-p.	5,614	1, 2, 3, 9, 11, 13, 15, 21, 24, 32, 36, 38, 46, 39
Miller Light, can, 18-p.	4,166	4, 5, 8, 12, 14, 17, 18, 39, 43, 44, 45, 47
Coors Light, can, 18-p.	3,560	19, 33, 42
Michelob Ultra, bott., 18-p.	3,054	6, 10, 31
Sam. Adams Season., bott., 12-p.	2,678	50, 51
Shipyard Season., bott., 12-p.	1,053	32
Miller High Life, bott., 18-p.	959	7

1.5.6 Application of the Dynamic Optimization

In this section, we analyze the incremental profitability of the dynamic optimization with a numerical example using the same profit margins π_{jt} as in the static optimization in Section 1.5.2. Table 1.13 summarizes the results where the previously discussed sets of constraints are enabled. Since the dynamic optimization is more restrictive in nature, it typically results in profits smaller than those shown in the static optimization.

The most restrictive (among all scenarios) is Scenario 1, where a retailer can only use one product/display space per week; each beer product can only be displayed at most five weeks per year; every three weeks each product/display combination can only be used no more than once; and every time a retailer replaces one beer SKU for another SKU, they incur a changeover cost of \$5. In this case, the incremental profit is $\$6,752$ once an incurred \$255 total changeover cost is subtracted. The subsequent scenarios individually relax these constraints. Intuitively, the total incremental profits increase as we relax constraints. In Scenario 2, where the restrictions stay mostly the same but the retailer no longer incurs the changeover cost of \$5, the realized profit is \$7,007. In Scenario 3, we do not impose a constraint on the number of consecutive weeks that a given SKU can be placed on promotional display, and the realized profit is \$7,275. Finally, Scenario 4 only restricts the use of one product/display space per week, which by definition is identical to the scenario examined in our static optimization, resulting in an incremental profit of \$16,425.

Please note the changeover cost needs to be at the level of the difference between the incremental profits of the two most profitable SKUs to affect the SKU choice. If the difference in the incremental profits between the two most profitable SKUs is small, then the changeover cost may not affect the promotional display decision. For this reason, the changeover cost also prevents the optimization model from changing the promotional display recommendation when the differences in the incremental profits are small.

1.5.7 Dynamic Benchmark Comparison

We choose a benchmark for the dynamic case that is analogous to the benchmark for the static case. Again, we assume that the store manager has no prior knowledge of the incremental profits he can obtain from placing his products on display. In this case, a reasonable approach is to have an objective that maximizes total sales units (while still obeying the constraints). The static benchmark is not applicable because it violates the dynamic constraints (as listed in Scenario 1 discussed above). For example, in the benchmark of the static case schedule (Table 1.12), the manager chooses bottled Bud Light (18-pack) nine weeks in a row (i.e., it is the highest seller in weeks 22-30). This violates the sparsity constraint and total weeks on display, i.e., Constraints (1.11) and (1.12), respectively. Due to the need for a benchmark to satisfy the constraints, we use an integer program to choose the benchmark solution. Specifically, we choose our objective function to maximize the sales units as being the analog of the benchmark for the static case. We take the solution obtained from using this objective function and calculate the actual incremental profits produced by this solution. For comparison purposes, the scenario constraints imposed for the benchmark are identical to the Dynamic Optimization.

Table 1.13: Profit Comparison for Dynamic Optimization and Dynamic Benchmark

Constraint	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4** (same as Static)
Total Display/Products per Week (only one display in each of 52 weeks)	✓	✓	✓	✓
Total Weeks on Display per Product (a product can be displayed at most five weeks in the year)	✓	✓	✓	
Sparsity (each product cannot be displayed more than 3 consec. weeks)	✓	✓		
Changeover Cost ($5)	✓			
Dynamic Optimization				
Incremental Profit	7,006.58	7,006.58	7274.64	16,424.63
Changeover Cost	-255	0	0	0
Final Incremental Profit (Profit minus Changeover Cost)	6,751.58	7,006.58	7,274.64	16,424.63
***Dynamic Benchmark**				
Incremental Profit	4,446	4,446	4,253	8,255
Changeover Cost	-255	0	0	0
Final Incremental Profit (Profit minus Changeover Cost)	4,191	4,446	4,253	8,255

In all of the benchmark scenarios, the profits are smaller than those obtained through the Dynamic optimization (Table 1.13). The dynamic optimization yields significantly higher incremental profit than the benchmark under the same conditions.

Note that the value of the objective function (not shown here) – total units sold – is always increasing as the constraints are relaxed. Our results corroborate the importance of estimating sales lifts and calculating incremental profits to facilitate promotional display space SKU-selection as opposed to simply selecting best-selling SKUs.

1.6 Conclusion

Optimizing product selection for promotional display space is an important lever that grocery store managers have at their disposal to influence customers' purchasing decisions and increase the profitability of their stores. In this study, we provide a decision support tool for choosing which SKUs to place on special promotional display spaces (such as end-of-aisle displays) inside a grocery store. Our methodology allows a retailer to choose a SKU for each promotional display space that results in the largest improvement in incremental profit for that particular store location.

Historically, retailers have identified which SKUs to put on promotional display spaces using simple heuristics, such as picking a best-selling SKU or the same SKU that was assigned on display during that time period the previous year. Our methodology offers several improvements over these existing practices. Our methodology proposes an estimation technique for measuring the incremental lift in sales of placing a particular SKU on promotional display space. These incremental lifts (represented by estimates of the percent increase in sales) are estimated using a sample from a national grocery store sales transaction dataset (collected by IRI), which allows us to estimate the sales lifts from a much larger set of SKUs than if the estimates were made using only the transaction data from a single store or store chain. This allows us to even estimate the sales lift for SKUs that have never been put on promotional display at a particular retailer. Our estimation methodology is capable of handling an extensive and complex product assortment and captures important aspects of promotional activities such as cannibalization of the inner aisle sales and halo effects. Our methodology also includes an optimization model for selecting which SKUs to put on promotional display for each individual store. The optimization model includes the incremental lifts (from the estimation method) combined with the estimated base-sales rates and profit margins of each SKU so that the profit-maximizing SKU can be chosen for a promotional display space for each week of the year. Our optimization model is also flexible enough to consider several practical aspects such as common business rules that restrict the selection of the same SKU over a consecutive set of weeks, display-related changeover costs, and trade fund deals, which can provide grocers with additional profit through agreements with manufacturers concerning the placement of the manufacturers' products on promotional displays.

To demonstrate our methodology, we use retail CPG sales scanner data from multiple stores across different grocery store chains in New England. For illustration purposes, we use the beer category and focus on the optimization of major promotional displays for a given store within our dataset. We find that assigning a SKU on promotional display can result in a significant lift in sales. For instance, we estimate an average sales lift of 27% across all SKUs, confirming that promotional display is a very effective tool for stimulating incremental product sales. We then compare the profitability of our proposed approach with a common industry benchmark. Our benchmark selects the best-selling SKUs per week to be placed on a promotional display under the assumption that a store-manager has full information regarding which SKUs will be best-selling for the incoming week. We find that our approach significantly outperforms this common practice, resulting in an incremental profit improvement of an 1.6X to 2X improvement, depending on the business rule constraints imposed by the store.

Our study identifies several opportunities for future research. We have focused on the selection of SKUs to be placed on a promotional displays assuming that product categories have already been assigned to displays and in Appendix 3.5 we discuss how our methodology can be extended to select SKUs across different product categories. An empirical example of such an extension will require the use of market basket data, which we did not possess. Another future research opportunity would be to develop an estimation model that would capture the decay of the display lift over time. As with many types of promotions, the lift from a display promotion can diminish over time if the display continues to have the same item. A model that incorporates the decay of the display lift would identify when to switch a promotional display to a new SKU so that a store manager does not have to rely on specific business rules to make such a decision.

Chapter 2

Estimating Consumer Decision Trees Using Aggregate Sales Data Without Identified Customers

2.1 Introduction

Due to shifting consumer preferences, stronger competition from stores like Aldi and Trader Joe's, and rising real estate prices (Mani et al 2016), major retailers see their competitive strength coming in the form of a smaller store format [Wahba, 2017, Tuttle, 2014]. Publix just announced a plan to open smaller-scale stores "taking aim at growing competition"[Arnold, 2018]. At 28,000 feet, such stores are more than twice smaller than regular Publix stores. New Walmart's Neighborhood Markets are now roughly 80% smaller than Walmart Supercenters [Crowe, 2015]. Target's recently opened Queens, NY location is about 85% smaller than "normal" [Gustafson, 2015]. Kroger's Turkey Hill Minit Market store in Columbus, OH is roughly 89% smaller in size than an average Kroger location [Tuttle, 2014].

Amidst product proliferation [Bayer et al., 2013] and high turnover [Chong et al., 2001], one of the biggest challenges for brick-and-mortar retailers in such environment is to understand how to reduce product clutter, and, thus, identify the most effective product assortments to carry. Studies show that consumers welcome "the elimination of clutter brought on by the reduction in redundant items" [Boatwright and Nunes, 2001], but the path of shrinking a store assortment from a traditional Walmart-size (i.e. 40,000 SKUs) to, say, the size of Aldi (i.e. 1,400 SKUs) [Meyersohn, 2019] isn't that straightforward. For example, simply eliminating low-selling items from assortment, also known as "cutting-the-tail" technique, risks letting buyers no longer find a preferred item [Broniarczyk et al., 1998]. How can a retail manager identify the most effective product assortment amidst increasingly scarce shelf-space?

In this paper, we develop a systematic, data-driven methodology to empirically identify attribute-based product demand structures, also known as decision trees to identify a "stylized" process by which a typical decision-maker arrives at a final purchase decision [Shocker et al., 1991, p.182] using retail scanner data. Decision trees help narrow down the pool of most essential products by identifying competitive product sets and the degree of their substitutability among each other. Using this information, a store manager can decide which product attributes can be dropped from the assortment, and, furthermore, which particular SKUs must be kept.

While a vast number of studies in both marketing and operations management research assume retail decision tree structures, limited attention exists on developing algorithms that allow to identify, estimate, and evaluate the demand structure using actual retail data. Vastly available sales transactions data can turn decision trees into an accurate and efficient tool to help retailers identify most profitable product assortment. We complement the empirical stream of operations literature by offering a decision support tool to help determine data-informed multi-level demand structures (i.e. decision trees). We use scanner purchase data across multiple markets and multiple stores, which involves a larger pool of customers and products is used in this study. Also, as our methodology extends beyond a single store into multiple stores, it allows to break away from the current assumptions of fixed product choice and consideration sets within and between stores. Using information on product attributes from actual beer sales data, our tree identifies the rank of importance of these attributes including brand, container type, package size, and calorie intensity. During the final stage of the analysis, an actual SKU to retain in the assortment is chosen. In addition, our work also empirically identifies product submarket structures, where such information that can be used in analytical assortment and price optimization literature, where the nested structure of submarkets is typically assumed to be known a priori.

The rest of the paper is organized as follows. In Section 2.2, we review the relevant literature. In Section 2.3, we describe our methodology and the data used. In Section 2.4, we apply the methodology and discuss the empirical results. In Section 2.5, we conclude the paper.

2.2 Literature Review

Historically, product demand structure has been studied and depicted in the form of nested submarkets, also known as decision trees [Rao and Savabala, 1981, Grover and Dillon, 1985, Kamakura et al., 1996, France and Ghose, 2016]. In a typical decision tree, the first root node represents an entire population of options and is sub-divided into a set of intermediate nodes representing grouping criteria, which in turn are sub-divided into a set of terminal nodes representing the final decision [Friedl and Brodley, 1997]. Each intermediate node has only one ascendant node and two or more descendant nodes. Hence, each subsequent selection of products is nested and thus conditioned upon the previous selection. It is assumed that objects are relatively more homogeneous within the subsets and relatively more heterogenous between the subsets, thus subsequent division results in increasing competition[Rao and Savabala, 1981].

An illustration of an attribute-based decision tree is shown in Figure 2.1. Here, the ordering of attributes is not the same on every branch, as branches can be different in their structure, otherwise, a simple ordering of the attributes wouldn't require a decision tree. For simplicity, we consider all beers in Brand A. This structure shows that those who prefer bottled beers further care about calorie intensity, whereas those who like canned beers, consider the product size first and then the calorie intensity. Note that for the bottled beers, the branch stops at the level of calorie intensity. It means that beyond these attributes, shoppers become indifferent about other product attributes. For the canned beers, only those in size 12 per pack further divide into two subgroups based on calorie intensity, light and regular. For the sizes 6- and 18-pack, calorie intensity doesn't matter, thus, the branch ends there.

Once the manager determines the nested structure of the consumers' decision-making process, one can expect a significant difference in a store's product assortment. For example, if the manager determines that calorie intensity has a stronger importance than size of the package in their store, they will put more emphasis on ensuring calorie-related variety, while keeping size selection constant. However, if the manager determines that product size has a bigger importance than calorie-related variety in their store, the manager may expand the diversity of product sizes instead.

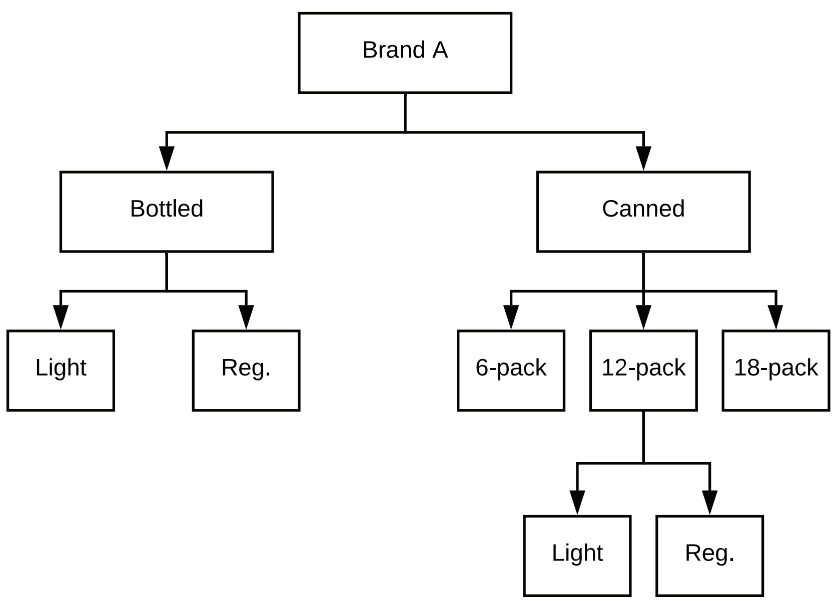

Figure 2.1: Sample Tree

Brand switching-based decision trees. Studies like Rao and Savabala [1981], DeSarbo and De Soete [1984], Novak [1993], Kannan and Sanchez [1994], Grover and Srinivasan [1987], France and Ghose [2016] build decision trees by using brand-switching data. Assuming homogeneous customers, Rao and Savabala [1981] propose and test a methodology for understanding the hierarchy of a consumer choice process. They are one of the first to propose a methodology to empirically determine consumers' choice by assuming a potentially sequential nature of the decision making process. They propose "a hierarchical non-overlapping structure, consisting of several nested partitions where an item may belong only to one partition at a given level based on a set of product attributes. The methodology consists of nine distinct steps that include identification, testing, interpretation, and comparison of the hierarchical structures that best represents the observed data." Using longitudinal purchase data from 768 households, they derive the optimal hierarchical decision-making structure for soft drink purchases. However, this methodology does not account for product price and price promotions, and according to Allenby (1989), lack any economic theory behind it. The substitutability between the items is already embedded in the brand-switching data. DeSarbo and De Soete [1984] extend Rao and Sabavala (1981) "by introducing a new type of hierarchical clustering procedure purposely designed to accommodate non-symmetric proximities." Their method, they argue, works like a traditional hierarchical clustering method, which are applied to an upper-triangular half, lower-triangular half, and averaged normalized transition matrix, and comparing the resulting solutions. Urban et al. [1984] develop a set of statistical procedures to define the aggregate competitive structure of a market, where they test whether a product market can be divided into a set of submarkets based on competing measures (product attributes, user characteristics, or product usage), and which alternative measure of submarkets describes the aggregate market structure best at any given time. The assumption is that members of submarkets are competing with each other within the submarket. France and Ghose [2016] extend Urban et al. [1984] by identifying optimal submarket configurations using large datasets and their visualization (essentially, performing big data maps). Using two data types – switching probabilities and attribute ratings – the authors form a market structure model.

In contrast to retail scanner data, brand switching data has some restrictions. In order to obtain brand-switching data, repeat consumer-level purchases are required. Even when such data is available, brand-switching models tend to have trouble incorporating the impact of price promotion on brand-switching activity [Allenby, 1989]. Additionally, brand-switching data can be inaccurately calculated in the case of simultaneously purchased brands [Day et al., 1979].

Behavioral household data- & focus-group/survey-based decision trees. Alternatively, other studies [Ramaswamy and DeSarbo, 1990, Currim et al., 1988, Kannan and Wright, 1991, Kamakura et al., 1996] use behavioral household data to empirically determine multi-level trees. Behavioral data sets tracks household panel purchases, which can be difficult or expensive to obtain McFadden et al. [2005]. Additionally, purchases can be biased toward earning-seeking, lower-income households who agree to participate in such panels. Kannan and Wright [1991] and Kamakura et al. [1996] assume structural heterogeneity across consumers (i.e. each consumer has their own decision tree). This assumption limits the practical relevance of their method since in a brick and mortar store setting, the retail manager cannot customize their assortment for each customer. Instead retail managers need to provide a general assortment portfolio for all of their customers. Another set of papers like Urban et al. [1984] uses focus group feedback or vendor surveys [Hui, 2004].

Aggregate scanner data-based decision trees. The core paper relevant to our research is Allenby [1989], who, although doesn't build an actual tree, offers a way to evaluate a single-level demand structure using retail scanner data (in other words, it only looks at the first level of the tree). Assuming that products are nested within brands, and brands are nested within a product category, he shows that products can be grouped into submarkets using retail scanner data. What sets his work apart from existing literature is that Allenby [1989] offers an efficient empirical estimation of cross elasticities, thus, accounting for substitution effects across all products. He evaluates "similarities" and "dissimilarities" by expoliting information about product attributes in the data. This approach has several advantages–it is based on an explicitly stated economic theory of consumer random utility models, can be applied to both static and dynamic settings, can be tested on existing scanner data, has the flexibility to generate hypotheses and test hypotheses, and leaves room for working with competing clusters of brands. While the theory of random utility models is relatively easily generalizable and is applied to linear probabilistic models of discrete choice sets, the main novelty in Allenby's (1989, 279) solution was the explicit assumption that the stochastic parts of certain products are correlated. An assumption that the market consists of products with correlated error structures is both theoretically and practically reasonable and realistic. Therefore, by utilizing the characteristics of brands, one may generate a matrix of product cross-elasticities within and between submarkets. A prominent contribution of the Allenby's work is the practical reduction in the number of cross-elasticities. Typically, the estimation of ordered, individual cross-effects requires the calculation of the matrix of cross-price elasticities, which can limit the number of products that can be used in the analysis due to the quadratic nature of the matrix. Allenby found a way to reduce the number of cross elasticities needed to characterize the market by 95% (in his example, the number of cross elasticities reduced from 90 to 4) [Allenby, 1989, p. 271].

However, to capture cross-effects, Allenby's approach makes a simplified assumption that assortment never changes (cross-price elasticities are presented as a constant-elasticity matrix). The constant-price elasticity matrix requires that all items are always selling and always have a price (i.e. no item is ever removed). On the one hand, his analysis is performed at the brand-level, and brands are rarelly added or dropped from assortment, especially in the narrow category he is studying, which is toilet paper, which makes the assumption relevant if one studies brand-level markets. On the other hand, in the vastly available scanner data, SKUs are frequenty added/dropped from the assortment by the retailer, which impacts the frequency of assortment changes across brands and product categories. Hence, the estimation of SKU-level cross-elasticities has to handle frequent assortment changes. As we can no longer use Allenby's approach of accounting cross-elasticities, we use a model which does not have the restriction on keeping the set of items the same. Specifically, we adopt [Rooderkerk et al., 2013] of capturing similarity among SKUs using retail scanner data and an attribute-based metric. Rooderkerk et al. [2013] introduce an attribute-based demand estimation model and account for product substitution by using attribute-based similarities between the products. Hence, we are build upon Allenby's (1989) methodology in two distinct ways. First, we extend his approach to an actual SKU-focused decision tree structure, and second, using an improved way of capturing cross-effects that doesn't limit the number of products to consider in the analysis.

Additionally, most studies with the exception of Allenby [1989], Currim et al. [1988], Kannan and Wright [1991], Kamakura et al. [1996] assume that the decision tree structure is given or fixed. Studies assuming fixed decision tree structures in different segments of customers, where a typical decision tree structure is assumed to be of a particular order, argue that the choice of a product type is followed by the choice of a brand within the product type (Hui 2004, Chen and Yang 2007, Rao and Savabala 1981, Kannan and Sanchez 1994). A generic assumption like this may not reflect a true and dynamic decision tree structure. With modern proliferation of various products that compete with established brands within their product category, it is no longer clear which product attributes drive current day consumer choices (i.e. package size, sold on discount, etc.).

Other methods. Although sharing a structural resemblance, a decision tree is not the same as a dendogram, which is a visual representation of a similarity matrix using machine learning techniques. Dendograms tend to be overcrowded with tree branches and, thus, hard to read because n products must be represented by $n-1$ nodes. Finding a dendogram solution can be computationally challenging if the number of SKUs exceeds a certain threshold. This is not the case with decision trees, where the number of nods depends on the number of grouping attributes. Additionally, dendograms cannot explain which criteria are used in the creation of branches and sub-branches.

Support for analytical work. Recently, the assortment and price optimization literature in operations research started to incorporate multi-level product structures intro their modeling techniques, where the nested structure of submarkets is typically assumed to be known a priori. For example, in a two-nested structure (e.g. Kok and Xu [2010]), customer sequentially first, chooses a product category and then, a specific brand, or has an option of first, choosing brand and then, a specific product within the brand. Other select assortment and price optimization studies that employ two-nested structure include Davis et al. [2014], Gallego and Topaloglu [2014], Li and Rusmevichientong [2014], Gallego and Wang [2014][1].

Also, most recently, a new stream of literature has emerged that extends analysis beyond two levels into d-level structures, where the decision tree is of depth d. Li and Tellis [2015] allows each product to be described by d-number of features. Similarly to logic of the two-level nested structure, the product selection process is described as a sequential d-step process where the customer narrows down the selection of products

[1]A detailed review of various nested multinomial models that have been proposed for the assortment planning problem are reviewed in Berbeglia et al. [2018].

by choosing the first feature, and then with each subsequent selection of features the choice of products narrows down to a single product.[2] [3] Due to the arbitrary nature of the submarket structures, it is assumed that the end-user of the model knows how to determine these submarket structures across nests. This work seeks to help the end-user determine these structures when applying the aforementioned analytical work to practice. We further discuss a body of empirical literature that has contributed to a better understanding of market structures and decision trees in a retail setting.

Table 2.1: Select Literature

	Homogenuous consumers	Multilevel decision tree structure	Data used (brand-switching data, survey, scanner)
DeSarbo and De Soete (1984)	✔	✔	brand-switching + experiment with 280 students and secretaries
Rao and Sabavala (1981)	✔	✔	brand-switching
Novak (1993)	✔	✔	brand-switching
Kannan and Sanchez (1994)	✔	✔	Brand-switching
Grover and Srinivasan (1987)	✔	✔	brand-switching
France and Ghose (2016)	✔	✔	brand-switching
Ramaswamy and DeSarbo (1990)	✔	✔	household panel
Currim et al (1988)	✔	✔	household panel
Kannan and Wright (1991)		✔	household panel
Kamakura et al (1996)		✔	household panel
Urban et al (1984)	✔	✔	other (focus groups)
Hui (2004)	✔	✔	other (vendor surveys)
Allenby (1989)	✔	Single	Scanner
Rooderkerk et al. (2014)	✔	N/A	Scanner
This paper	✔	✔	Scanner

[2]This stream of literature is different from the sequential multinomial logit model Flores et al. [2018], where the consumer first looks at one group of products (e.g. those that are promoted), and then decides on the purchase of a separate group of products (e.g. those that are regular-priced). Here, the decision to buy something depends on the promotional/price activities for the other products.

[3]It is also different from MNL with nested consideration sets Feldman and Topaloglu [2015]. Here the consideration sets of one customer type is included in the consideration set of a different customer type. The multinomial logit model captures the choice process of the both customer types accounting for the fact that customers of different types have different consideration sets.

2.3 Methodology

The methodology is a several-stage process, which is similar to the Allenby's general principle (i.e. determining the market structure by picking the best-fitting model). First, like Allenby's, our goal is to determine which submarkets can effectively describe the market as a whole. For this, we hypothesize that the market is composed of distinct submarkets of homogeneous products, and our task is to determine which specific product attribute best defines these submarkets. But unlike Allenby, we take a step further and seek to build a decision tree, where a homogeneous consumer continues to sequentially partition submarkets to the point until no attributes remain. Here, in each stage, we seek to determining the most appropriate submarket based on the several alternative submarket structures using the best model fit. To measure model fit and accuracy of each alternative model at each stage of the decision tree, we, like Allenby, report statistics like a likelihood test, AIC, and BIC.

In this section, we describe the econometric analysis. We break down our discussion in two subsections. The first subsection describes the sales response function, whereas the second subsection describes how the cross elasticity measurements are captured in the model. The cross-elasticity measurement is key to evaluating submarket information.

2.3.1 Econometric Model

We build an econometric model based on the widely used Scan*Pro model [Wittink et al., 1988, Foekens et al., 1994] that evaluates the log of weekly unit sales S_{jti} of a SKU $j \in \mathbb{U}$ (the consideration set of SKUs) and controls for seasonality and marketing-related activities (i.e., discounts, temporary price reductions, advertisements, coupons) at store i during week t. It is, however, a modified version of the model, as it also incorporates product cross-effects for an attribute g (the original model only included self-effects).

$$
\begin{aligned}
\ln S_{jti} \;=\;& \overbrace{\delta_0}^{\text{Intercept}} + \overbrace{\sum_{z \in \mathbb{U}} \delta_{1z} Z_{jz}}^{\text{SKU Effect}} + \overbrace{\delta_2 D_{jti}}^{\text{Display Effect}} + \overbrace{\delta_3 H_{jti}}^{\text{\% Discount Effect}} + \overbrace{\delta_4 P_{jti}}^{\text{Price Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{5t'} W_{t't}}^{\text{Week Effect}} \\
&+ \overbrace{\sum_{m \in \mathbb{M}} \delta_{6m} M_{jmti}}^{\text{Marketing Mix Effect}} + \overbrace{\sum_{m \in \mathbb{M}} \delta_{7gm} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} M_{j'mti}(1 - M_{jmti})}^{\text{Cross-Marketing Mix Effects for Attribute } g} \\
&+ \overbrace{\sum_{i'=1}^{I} \delta_{8i'} B_{i'i}}^{\text{Store Effect}} + \overbrace{e_{jti}}^{\text{Error Term}} \qquad (2.1)
\end{aligned}
$$

Here, we model the demand/sales of SKU $j \in \mathbb{U}$ at store i in week t as a log-linear model[4] given in (2.1) to capture how various factors like for seasonality and marketing-related activities (i.e., discounts, temporary price reductions, advertisements, coupons) impact product sales at store i during week t. Since the majority of grocery store purchases are done in smaller quantities, we log-transform the dependent variable (i.e., sales of SKU j at store i in week t) to mitigate the positively skewed distribution of sales in our dataset. Marketing mix instruments can be time-dependent [Mela et al., 1997] and vary by product [Blattberg and Neslin, 1990]. Our model includes weekly indicators that not only account for seasonality in the consumption of the product [Fok et al., 2007] but also for potentially unobserved weekly effects such as manufacturer advertising. It also includes SKU indicators. We control for the SKU's price both directly and indirectly through its percentage discount, also

[4]Our setting precludes the use of choice modeling as an estimation technique due to the following reasons. To estimate a traditional choice model, one must have data on revealed purchases at the individual transaction-level, along with the information on the full choice set of products available to a consumer at that moment [Train, 2003]. Even with a methodology that can accommodate aggregate data for a choice model [Berry, 1994], purchase information still has to be limited in size and scope, with a full choice set usually not exceeding more than 4-5 options. In our setting, the storesâĂŹ transaction data is only collected at an aggregate level (by firms such as IRI and Nielson), specifically, at the store/week/SKU level, and there are hundreds or even thousands of various SKUs available at the time for purchase.

referred by Nijs et al. [2001] and Raju [1992] as "promotional depth". We also include store dummies to control for store-specific fixed effects.

The modification to the original Scan*Pro model comes in the form of adding the cross-effects to the original model. In lieu of Allenby's matrix of constrained cross-elasticities, our model captures SKU's cross-effects, where the cross effects are moderated by the degree of similarity between SKUs [Rooderkerk et al., 2013]. This is in line with the assertion that promoted items through some marketing mix activities will have a stronger effect (either positive or negative) on similar than dissimilar (non-promoted) items [Rooderkerk et al., 2011, Tversky, 1972]. The metric to capture such similarity is attribute-based [Hardie et al., 1998, Rooderkerk et al., 2013]. Here, the similarity variable ($SIM_{jj'gti}$) explicitly accounts for the fraction of SKUs that share the same attribute g during each store-week pair. More precisely, the proposed metric possesses an important characteristic: "the similarity between two SKUs on a given attribute should not only reflect the similarity of their own attribute levels, in an absolute sense, but also vis-à-vis the full distribution of attribute levels in the assortment. In particular, if two items share the same level of a nominal attribute (e.g., package type), their perceived similarity should be stronger when their shared attribute level occurs less frequently" [Rooderkerk et al., 2013, p.703]. The definition of this similarity variable is given in (2.2)[5].

$$SIM_{jj'gti} = I\{A_{jg} = A_{j'g}\} \times \left(1 - \frac{\sum_{j''=1}^{J} I(A_{j''g} = A_{jg})}{N_{ti}}\right), \tag{2.2}$$

where $I\{A_{jg} = A_{j'g}\}$ indicates if the arguments hold true (1), or not (0); A_{jg} is the level attained by a SKU on attribute g such that $A_{jg} = m \Leftrightarrow A_{jgm} = 1$; N_{ti} is the

[5]Please note that an alternative definition of similarity was considered where the similarity of attribute levels among SKUs was also tested in a binary sense, i.e., without considering the full distribution of attribute levels in the assortment. In this case, attributes are classified as 1 (similar) or as 0 (dissimilar). However, the statistical fit is better with the former definition given in equation (2.2).

number of SKUs present in week t in store i. Thus, for every attribute of a product, we construct a similarity variable that accounts for the distribution of attribute levels at the store/week level. The similarity values for the observations that do not belong to a specific attribute are zero, thus $SIM_{jj'gti}$ varies between 0 (no similarity) and 1 (identical).

We next provide a simple illustration of how $SIM_{jj'gti}$ is constructed. Consider that for beer products, an important product attribute g is the calorie content, which classifies beer SKUs as light versus regular. If, at a single store/week level, 1 out of 4 beer SKUs is light, then the similarity of one light beer SKU to another light beer SKU (expression within the parenthesis in (2.2)) is $1 - 0.25 = 0.75$. Likewise, for the remaining 3 regular beer SKUs, the similarity of any pair of these beer SKUs is $1 - 0.75 = 0.25$.

One modification to the methodology proposed by Rooderkerk et al. [2013] is that we recognize that it makes little sense to obtain the substitution effect of SKU j on SKU j' or of SKU j' on SKU j when both products use the same marketing instrument, in the same week, since this approach reduces the marketing mix effect. Thus, unlike Rooderkerk et al. [2013], when a pair of SKU j and SKU j' both have the same marketing mix effect applied to them, we incorporate the terms $(1 - M_{jmti})$ into their respective similarities to keep the effect "undisturbed". As a result, when $SIM_{jj'gti}M_{j'mti}$ is multiplied by $(1 - M_{jmti})$, when both SKU j and SKU j' are on a marketing mix promotion, the overall similarity effect will be zero because $M_{j'mti} = 1$ and $(1 - M_{jmti}) = 0$. Thus, in our estimation model (2.1), the terms $\sum_{m \in \mathbb{M}} \delta_{9gm} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti}M_{j'mti}(1 - M_{jmti})$ measure the cross-promotional (including feature, price reduction, display) responsiveness across SKUs moderated by their attribute-based similarity using only a single attribute g. A summary of our notations is provided in Table 2.2.

Table 2.2: Description of Variables and Symbols

Variable	Description
$\ln S_{jti}$	log unit sales of SKU j for $j = 1, 2, \ldots, J$ in store i for $i = 1, 2, \ldots, I$ in week t for $t = 1, 2..., T$
A_{ja}	indicator variable, $= 1$ when SKU j is part of subcategory V_a
D_{jti}	indicator variable, $= 1$ when SKU j at store i in week t is put on display; 0 otherwise
$W_{t't}$	indicator variable, $= 1$ if $t = t'$; 0 otherwise
M_{jmti}	indicator variable, $= 1$ when marketing mix instrument $m \in \mathbb{M}$ is applied to SKU j at store i in week t
H_{jti}	size of price reduction in cents for SKU j at store i in week t
Z_{jz}	indicator variable for SKUs, $= 1$ if j equals SKU z; 0 otherwise (one "dummy" represents all "other" SKUs not included in the consideration set)
$B_{i'i}$	indicator variable, $= 1$ if $i = i'$; 0 otherwise
$SIM_{jj'gti}$	similarity of SKU j to SKU j' for an attribute g in week t and store i

2.3.2 Data description

For the empirical investigation, we use a sample of syndicated retail sales scanner data collected by IRI, known as the IRI Marketing Data Set [Bronnenberg et al., 2008], which covers a variety of retail outlets with more than 102 stores in total in the New England region. Focusing on the New England region reduces differences in beer demand/consumption due to differences in customer preferences across geographic locations and weather conditions. The dataset covers five US markets in the New England Region such as 'Boston', 'Hartford', 'Pittsfield', 'Providence', and 'Other New England'[6] for all fifty-two weeks of the latest available year, 2011, and is structured at a SKU/store/week level, with a total of 387,228 sales observations. We focus on the sales of beer/malt beverages since this product category is typically one of the most popular impulse buy purchases [Bell et al., 2009].

[6] Other New England markets besides Boston, Hartford, Pittsfield, and Providence.

As we choose to work with the beer product category in this study, beer products have a diverse set of attributes, which includes beer type, brand, size, calorie intensity, and type of container. Additionally, beer is also often price-, feature-, or display-promoted, which can have an additional impact on a purchasing decision. (Although we have a large diversity of different brands, in our analysis we are going to only use those brands that have a large number of observations (Coors, Samuel Adams, Budweiser, Michelob, Sierra Nevada, etc.).)

Due to a wide variety of package sizes sold (from single bottles to 36-can packs), we only consider the most popular package sizes: 6-, 12-, 18-, and 24-unit products. We exclude unusually expensive transactions with unit cost greater than $1 per ounce (e.g., Samuel Adams' Utopia at $150 per 24 oz. bottle). Additionally, we exclude oddly shaped and rarely purchased product packages like party balls and kegs. A summary of our dataset is provided in Table 2.3. The key product attributes are brand, package size, calorie intensity, and container type.

Table 2.3: New England Data Set Summary

Subcategory	**Observations**	**Unit sales**	**SKU count**	**SKU count on display**
Subpremium	35,653	149,554	59	10
Premium	80,699	720,379	75	45
Superpremium	70,830	332,791	85	44
Craft	116,008	632,439	352	105
Import	84,038	432,586	159	60
Total	**387,228**	**2,267,749**	**730**	**264**

2.4 Empirical analysis

Information on the four distinct product attributes is used to build the decision tree: calorie intensity (light or regular), container type (bottle or can), package size (6-, 12-

, 18-, or 24-pack), and brand type. At the each level of analysis, we test the sequence of importance of these attributes. To identify the most preferred model specification, we evaluate various fit statistics for competing cross-effects. We first evaluate log-likelihood differences and AIC/BIC between-model differences. We use the rule of thumb of the AIC and BIC difference greater than 2 for selecting a model [Mazerolle, 2006]. We also perform cluster-robust Vuong tests to evaluate the goodness of fit of non-nested models [Vuong, 1989, Wooldridge, 2010], where the best-fit model is selected based on the sums of squared residuals. At every level, in addition to the alterntive model specifications, each alternative model is compared to a corresponding base model that doesn't capture any substitution effects.

First level. In the first level of analysis, we seek to determine the first attribute consumers look at when deciding on the purchase of beer. Four distinct models which separately capture each of the four cross-effect alternatives, plus the base model are tested. Specifically, it is tested if: 1) Products of the same brand under study are close substitutes; 2) Products of the same calorie intensity are close substitutes; 3) Products of the same container type are close substitutes; and 4) Products of the same package size are close subtitutes. Test statistics (Table 2.4) strongly suggests that the best fit belongs to the brand-based identification of cross-effects over all alternative models as well as the base model. Specifically, nearly all alternative models are better than the base model, with the exception of the package size-based model, which is better than the base model at the 5.7% Vuong's p-value. There is no virtual difference between the model based on calorie intensity again the model based on container type. Both calorie intensity-based model, as well as container type are better than the package size-based. And the brand-based model dominates across package-size, container type, and calorie intensity-based models.

Table 2.4: First-level analysis

Similarity g	Obs. 435,348	AIC and BIC diff.	log-like. diff.	Vuong non-nest. t-score	Vuong non-nest. p-val
Calor. intens. vs. Base	435,348	-2,897	1,452	-3.90	0
Contain. type vs. Base	435,348	-3,507	1,756	-4.93	0
Pack. size vs. Base	435,348	-572	289	-1.93	0.057
Brand vs. Base	435,348	-9,305	4,656	-7.87	0
Calor intens. vs. Contain. type	435,348	609	-305	1.14	0.257
Calor. intens. vs. Pack. size	435,348	-2,326	1,163	-4.15	0
Contain. type vs. Pack. size	435,348	-2,935	1,467	-4.75	0
Brand vs. Calor. intens.	435,348	-6,408	3,204	**-4.14**	**0**
Brand vs. Contain. intens.	435,348	-5,798	2,899	**-4.17**	**0**
Brand vs. Pack. size	435,348	-8,733	4,367	**-7.19**	**0**

Second level. Once the model fit estimates show that the most preferred model is based on brand information, the first level of our tree is set to Brand. We proceed by determining as to which attribute must be set for the second level of analysis, once a brand type is chosen. For this, we analyze each of the available brands separately. For illustration, we focus on 5 top selling brands in the Premium beer category, such as Bud Light, Budweiser, Coors Light, and Miller Lite, and Budweiser Select[7], as they are more likely to be substituted among each other (observations data is provided in Table 2.5).

Thus, we test which one of the three remaining cross-effect measurements (calorie intensity, container type, or package size) are appropriate for each forementioned brand for the second level of the tree. At this level of analysis, we test 16 models.

[7]Budweiser Select has a completely different positioning from Budweiser, including different logo, different fonts, and different colors used, hence, we make a distinction between these two brands.

Table 2.5: Top five brands in the Premium beer category

Brand	Number of Obs.	Obs. %
Bud Light	16,515	3.79
Budweiser	16,125	3.70
Coors Light	15,798	3.63
Miller Lite	14,600	3.35
Budweiser Select	6,699	1.53

Bud Light, Coors Light and Miller Lite only come in the light format, hence, for these brands, we do not evaluate the cross-effects based on calorie intensity (i.e. light vs. regular). Hence, these brands are being tested on whether 1) Products of the same container type are close substitutes; and 2) Products of the same package size are close substitutes. Budweiser only comes in regular (i.e. nonlight), thus, this brand is also being tests on whether 1) Products of the same container type are close substitutes; and 2) Products of the same package size are close substitutes. Budweiser Select is being tested on all the three similarities: 1) Products of the same calorie intensity are close substitutes; 2) Products of the same container type are close substitutes; and 3) Products of the same package size are close substitutes. Plus, for each brand, we test five base models (one for each brand).

The results of the second-level analysis for each brand are provided in Table 2.6[8]. For the brands Bud Light and Budweiser, the best model fit belonds to the container-based identification of cross-effects. Here, container-based models perform better than the base and the package size models. Hence, the empirical evidence here suggests that consumers of the brands Bud Light and Budweiser first decide whether they prefer bottled or canned beer; and the rest of the beer attributes for these brands are considered later.

[8] CT - container type, CI - calorie intensity, PS - package size.

For Coors Light and Miller Lite, there is no statistical difference between container type and package size, which are, however, notably better than the base model. It means that although the both types of the cross-effect calculation yield statistically siginificant results, neither is better than the other. This prompts us to test whether customers care about these two features simulatenously when choosing a product within these brands. For these two brands, we test a model that contains the both types of cross effects (i.e. container type AND package size) and compare this model to the (1) container type only model, (2) package size only model, and (3) base model. We find that the model with simultaneous consideration of the two attributes yields a statistically significant result that is better than any of the single-attribute models or the base model. Thus, we conclude that the customers place equal importance on the container type and package size features when shopping for Coors Light and Miller Lite products and, thus, consider them simultaneously. In other words, for Miller Lite shoppers, a canned 6-pack is equally important for consideration as a bottled 6-pack. (See the “Stopping criteria" and “Final nod selection” paragraphs below for further discussion).

Finally, for Budweiser Select, there is no sufficient evidence that buyers put a priority on the product features, as none of the models tested to identify the second level of the tree perform better than the base model. In practice, it means that people are only concerned if the beer is Budweiser, and there is no additional dominating attribute within this brand. In such cases when other attributes are not statistically different from the base model, the process of expanding a node stops since we can’t find any more significant attributes. (See the “Stopping criteria" and “Final nod selection” paragraphs below for further discussion).

Third level. We further continue construction of the tree by focusing now on the brands Bud Light and Budweiser, as for these brands there is still the package size left to test. In this case, we test eight models. Separately for canned Budweiser, bottled Budweiser, canned Bud Light, and bottled Bud Light, we test if the package size is an important attribute, and compare each model to its respective base model (i.e. a base model for each brand/container type combination). Statistical analysis (Table 2.7) suggests that for bottled Bud Light, canned Bud Light, and canned Budweiser, package size-based cross effects are not statistically different from the base model, which means that package size is not important for consumers. However, for bottled Budweiser, the package size-based cross-effect is a statistically significant attribute. In other words, package size is the last significant level of consideration for the bottled Budweiser.

Final nod selection. This tree building excerise has resulted in seven tree branches, specifically: 1) Bud Light-bottle, 2) Bud Light-can, 3) Budweiser-bottle-package, 4) Budweiser-can, 5) Coors Light-package size&container type, 6) Miller Light-package size&container type, 7) Budweiser Select. Since all the levels of attributes are now identified, we proceed to the last step of determining a specific node within a chosen branch the retailer should use.

In the case of the Budweiser-bottle-package branch, we further consider which specific size (6-, 12-, 18-, or 24-pack) to choose. During this step, we build and analyze four distinct models (one for each of the package sizes) and compare them to the base model. Each model is run within the bottled Budweiser brand. This time, each package size is treated as an attribute, hence package size-based cross-effects are calculated and used in the model, whereas the base model captures no cross-effects. The result (Table 2.8) indicates that the 6-pack generaly dominates all the alternative models, including the base. We conclude that the package size of 6 for bottled Budweiser should be prioritized by retailer to keep *(UPC-A 0 18200 00834 4)*. For Budweiser in cans, the top pick is the 18-pack *(UPC-A 0 18200 11218 8)*.

For the brands Coors Light and Miller Lite, as deterined earlier, there are 8 possible combinations of package size and container type (four package sizes X two container types). We suggest the retailer to choose at least one combination per each brand. A criteria for choosing a product can be its level of popularity. We suggest that one of the measures of popularity can be the total sales units of the product. For Coors Light, this is bottled 18-pack *(UPC-A 0 71990 30078 4)*. For Miller Lite, this is canned 18-pack *(UPC-A 0 34100 57340 9)*.

For Bud Light-bottle, the most popular item is 18-pack *(UPC-A 0 18200 53308 2)*. For Bud Light-can, it is 18-pack *(UPC-A 0 18200 53218 4)*. For Budweiser-can it is 18-pack *(UPC-A 0 18200 11218 8)*. Finally, the most popular item for Budweiser Select is 18-pack, can *(UPC-A 0 18200 96244 4)*. The branches and final nodes are illustrated in Figure 2.2.

The tree depicts how the attributes in the beer category matter to the consumers based on sales data. The "insignificant" attributes indicate that consumers don't distinguish between those features, hence, one can resort to carrying the most popular products.

Branch termination. Because there is a finite number of attributes, a branch must come to an end. However, the branch can end earlier when none of the attributes are statistically siginficant.

2.5 Conclusion

Current business tendencies toward a smaller store format among grocery retailers make it more difficult for a store or chain manager to determine the most essential product assortment to carry due to tighter space limitations and the current proliferation of products with various attributes. We offer a systematic, data-driven

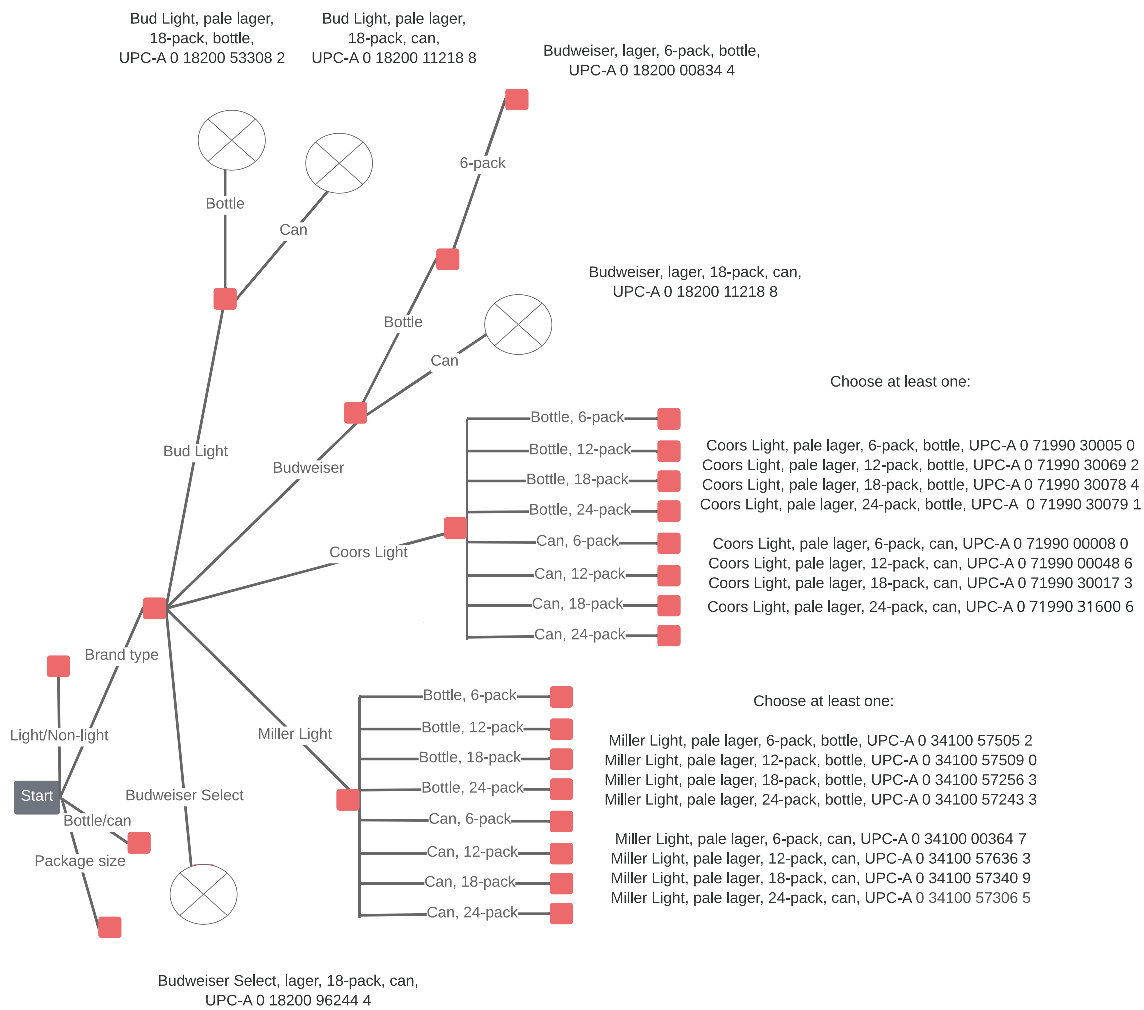

Figure 2.2: Decision Tree

methodology to empirically identify attribute-based product demand structures, also known as decision trees, that can help to narrow down a large attribute-based pool of products to a most essential subset a store manager needs to carry. Our methodology carefully identifies the importance of product attributes and accounts for attribute-based substitution across products.

Using a large sample of beer sales across the US, we identified that the costumers first care about the brand information when they seek to purchase beer. first look at the brand information of the beer. Once the brand is chosen, each brand has a unique path toward the final choice of a product. In our empirical demonstration of the five top-selling brands Bud Light, Budweiser, Budweiser Select, Coors Light, and Miller Lite, the decision tree creates a path toward identifying the final five products out of a total of 53 that belong to these five brands. We show that brands don't tend to have identical tree branches, meaning that consumers set attribute priorities differently for each brand. Hence, for a retailer store manager this information might serve as a guidance when determining which products to retain in the assortment.

Additionally, based on our work, one can empirically identify product submarkets and use this information in analytical assortment and price optimization literature, where the nested structure of submarkets is typically assumed to be known a priori.

Table 2.6: Second-level analysis

Brand	Similarity g	Obs. 435,348	AIC/BIC diff.	log-like. diff.	Vuong non-nest. t-score	Vuong non-nest. p-val
Bud Light	CT vs. Base	16,515	233.19	-466.37	-3.87	0
	PS vs. Base	16,515	20	-39.99	-0.78	0.438
	CT vs. PS	16,515	213.19	-25287.95	-3.72	0
Budweiser	CT vs. Base	16,125	511.48	-1022.97	-5.46	0
	PS vs. Base	16,125	94.07	-188.15	-1.77	0.082
	CT vs. PS	16,125	417.41	-834.82	-4.81	0
Coors Light	CT vs. Base	15,798	419.59	-839.2	-4.16	0
	PS vs. Base	15,798	288.52	-577.05	-2.73	0.009
	CT vs. PS	15,798	131.07	-262.15	-1.23	0.223
	CT&PS vs. Base	15,798	595.85	-1191.72	-4.25	0
	CT&PS vs. CT	15,798	176.26	-352.52	-2.35	0.023
	CT&PS vs. PS	15,798	307.33	-614.67	-4.11	0
Miller Lite	CT vs. Base	14,600	327.95	-655.91	-3.36	0.001
	PS vs. Base	14,600	337.52	-675.06	-3.22	0.002
	CT vs. PS	14,600	-9.57	19.15	0.1	0.924
	CT&PS vs. Base	14,600	534.33	-1068.66	-3.93	0
	CT&PS vs. CT	14,600	206.38	-412.75	-2.74	0.008
	CT&PS vs. PS	14,600	196.81	-393.6	-3.07	0.003
Budweiser Select	CI vs. Base	6,699	14.053	-28.107	-1.78	0.081
	CT vs. Base	6,699	12.874	-25.747	-1.72	0.092
	PS vs. Base	6,699	20.252	-40.504	-1.35	0.183
	CI vs. CT	6,699	1.179	-2.36	-0.13	0.895
	CI vs. PS	6,699	-6.199	12.397	0.42	0.68
	CT vs. PS	6,699	-7.378	14.757	0.6	0.553

Table 2.7: Third-level analysis

Brand & Package size-based cross effects	log-likelihood difference	AIC and BIC difference	Vuong's m t-test	Vuong's p-value
Bud Light, bottle vs. Base	28.33	-56.66	-1.24	0.22
Bud Light, can vs. Base	137.81	-275.63	-1.71	0.09
Budweiser, bottle vs. Base	**303.29**	**-606.59**	**-3.07**	**0.00**
Budweiser, can vs. Base	6.88	-13.77	-0.76	0.45

Table 2.8: The choice of the node within the last level of analysis

Brand Models	log-likelihood difference	AIC and BIC difference	Vuong's m t-test	Vuong's p-value
6-pack vs. base	28.568	-57.14	-2.25	0.029
12-pack vs. base	0.28	-0.56	-1.18	0.241
18-pack vs. base	0.099	-0.2	-2.10	0.040
24-pack vs. base	0.007	-0.02	-2.36	0.022
12-pack vs. 18-pack	-0.587	1.18	0.12	0.901
12-pack vs. 24-pack	-3.258	6.52	0.59	0.556
18-pack vs. 24-pack	-2.671	5.34	0.71	0.479
6-pack vs. 12-pack	55.853	-111.71	-1.98	0.053
6-pack vs. 18-pack	55.266	-110.53	-1.95	0.056
6-pack vs. 24-pack	52.595	-105.19	-1.94	0.058

Chapter 3

Retailer Strategies to Encourage Reduced Packaging Adoption

Optimizing Stock-Keeping Unit Selection for Promotional Display Space at Grocery Retailers

3.1 Introduction

When a young sperm whale washed ashore on a Spanish beach on February 27, 2018, surprised scientists discovered that his untimely death was caused by a ruptured digestive system filled with 64 pounds of trash and plastic debris [Diaz, 2018]. The much-publicized event was a grim reminder of the pervasiveness of plastic pollution—in the oceans, plastic bottles, bags, pellets, and fragments add up to 250,000 tons of floating waste, which marine life often mistake for food [Eriksen et al., 2014]. In fact, scientists estimate that out of 6.5 trillion tons of plastic materials ever generated to date by humans, only 21% has been either recycled or incinerated, and the rest ended up as waste in the environment [Geyer et al., 2017]. Declining oil prices and lax environmental regulations have turned plastic into a very popular packaging material [Wiener-Bronner, 2019] to the point that post-consumer plastic packaging waste is by far the largest source of plastic pollution. It is estimated that, in the US alone, 33 million tons of plastic packaging end up in landfills each year [EPA, 2016].

The alarming levels of plastic pollution have drawn renewed attention to the CPG manufacturers product packaging practices. It has been long established that reduced packaging improves operational efficiency for manufacturers who adopt it. For example, manufacturers can lower the cost of plastic packaging [Van Ewijk and Stegemann, 2016, p. 122], achieve gains in vehicle cube space (Goldsby and Martichenko, 2005; Hellstrom, 2007; Johnsson, 1998), shorten lead time "required for completion of packaging operations, which ultimately affects [...] due date performance (delivery) to the customer' ' [Saghir, 2004, p. 3], and achieve staffing efficiency due to less cumbersome process of "packing, lifting, carrying, lowering, and unpacking" [Goldsby and Martichenko, 2005, p. 49]. However, despite these seemingly obvious benefits, the practice of 'slack-filling', the use of an exceedingly large amount of packaging compared to actual product content, is still wide-spread [Hall, 2017, Spring and Earl, 2018]. For example, individual packaging for candy or chips sometimes exceeds the actual product content by nearly 100% [Zogby et al., 2018].

Often there exists a legitimate reason for slack-fill [Code of Federal Regulations, 2018]. Excessive packaging may prevent theft or loss of small but expensive products such as jewelry and accessories, USB sticks, computer memory cards, or batteries. Additionally, such packaging can offer extra protection to quickly spoiling food items (fresh produce wrapped in multiple layers of plastic) or to fragile products (screens, or glass products in general). Empty space might also inadvertently appear in packages with powdered substances since powder tends to settle during shipping and handling. Larger packaging might also be needed to accommodate moisture-absorbing cotton layers or mandatory Food and Drug Administration food labeling. Last but not least, high-end companies use excessively large packaging to emphasize product luxury and provide a premium sensory experience to the end-user (cosmetics, toiletry, perfume, cells phones). However, a recent wave of class-action lawsuits and commercial litigation allege that manufacturers "pack in" extra size for the sole reason of giving an end buyer the impression of a larger product volume [Zogby et al., 2018].

Analogously to dry snacks like chips, powders, or candy that "pack in" extra air to slack-fill, certain liquid consumer goods products may "pack in" extra water. Such practice is relatively easily noticeable in the category of water-based cleaning products such as laundry detergents. For more than two decades, CPG manufacturers have had access to concentrated liquid detergent technology that technically could have allowed significant packaging size reductions through water removal, while keeping the potency of detergent liquid the same. However, estimated to be a $5.20 billion market [Euromonitor, 2018], liquid laundry detergents are still generally heavier, wider, and taller than the majority of other consumer packaged goods, which in the past could be up to 90 %–water content [Corbett, 2014].

To understand other key reasons for why packaging reduction does not occur as often as desired, it is important to remember that in a traditional brick and mortar setting, consumer-product engagement occurs during an actual purchase. A consumer makes their final purchasing decision by simultaneously engaging with a set of products presented on a retailer's shelf space. Being aware of that, individual manufacturers use packaging also as a tool to grab consumer's attention in a highly competitive retail environment. An "interface between the product or brand and the consumer" [Lindh, 2016, p. 5], consumer packaging is designed to represent a product, protect it, and deliver a certain impression [Goldsby and Martichenko, 2005], at times costing as much as 30-40% of the product's retail price [Prendergast and Pitt, 1996]. Research has long established that oversized packaging might improve product visibility among competition (serving as an improvised display), and also give an impression of larger product volume (and supposedly better value) [Sloane, 1987]. This might offer insights as to why the laundry industry's transition to concentrates throughout the past several decades has been relatively slow. Recognizing the drawbacks of the smaller packaging, product manufacturers are reluctant to reduce packaging size amidst their fight for consumer's attention in a highly competitive environment.

Amidst ongoing product assortment expansion trends, where modern retailers can carry up to 300,000 SKUs [Breuer et al., 2013] and 'rapidly shrinking stores' [Bhattarai, 2017, Tuttle, 2014], oversized packaging for products such as laundry detergents creates significant logistical challenges for retailers such as shelf-space inefficiency, as they require more space for storage and display [Hellstrom, 2007, Goldsby and Martichenko, 2005]. Thus, the impact of reduced packaging on shelf-space efficiency can be quite meaningful. In a known non-detergent example, General Mills' Hamburger Helper was able to stock 20 percent more of the product on retail shelves nationwide (in addition to saving around 900,000 pounds of paper fiber annually) [Kapner, 2008]. Similarly, retailers improved their occupied cubic retail shelf space capacity when Kellogg changed the shape of their cereal boxes. Kellogg itself benefited from reducing its packaging material use by 8 percent [Reuters, 2009]. Consequently, for the environment, it can contribute to the preservation of natural resources like water since manufacturers can use less water in product formulation (as much as 5 million tonnes of water was used to produce detergent worldwide in 2015 [Euromonitor, 2018]).

In this work, we are exploring ways of how retailers can use their own levers of power to fix this problem. We distinguish between two distinct levers—one that retailers with significant market power may exert, and another that is available to a broad range of retailers, including those with relatively less market power. The first lever is wielded by retailers with significant market power such as Amazon or Walmart. There have been recent examples when these firms successfully pressured producers to shrink the size of their plastic packaging. Reports show that the manufacturer of Tide and Seventh Generation has changed their Amazon-bound laundry detergents to lighter packaging in order to "please Amazon and other online retailers" [Pisani, 2018]. Recently, Amazon reported that it spent $22 billion on shipping expenses [Amazon.com, Inc., 2018]; so, understandably, lighter product weight would help mitigate that cost. Similarly, Walmart, the biggest retailer in the world according to Forbes [Carbonara, 2018], officially mandated all US and Canadian detergent producers to supply concentrated versions of their products, which would have resulted in market-wide implications. In cases of non-compliance by manufacturers, the store threatened with a range of sanctions, which in the worst-case scenario could result in being dropped from the retailer's shelves [Walmart, 2007, 2008, Spicer and Hyatt, 2017]. As levers go, this is a rather direct one, primarily aimed at manufacturers.

However, few retailers have the power to replicate Amazon and Walmart's impact. A lever that they can utilize, alternatively, is to incorporate consumer nudging toward certain product choices or product characteristics, an economic theory well-summarized and widely popularized by Thaler and Sunstein [2009]. "A nudge is a term used to describe any change in the environment, which steers an individual's behavior in a predictable way while preserving their freedom of choice. It's not a push nor a shove, but a gentle nudge" [Catchpole, 2018]. This research stems from early work by Kahneman and Tversky [1979], who argued that individual preferences are often triggered by inputs from their surroundings. To the best of our knowledge, this notion is yet to be sufficiently explored in a retail operational context, and as recently underscored by Donohue et al. [2019], is a promising choice architecture technique to improve decision processes and outcomes in operations research. The most notable successful applications of nudging have been attained in on-line retailing [Weinmann et al., 2016], marketing [Burchell et al., 2012], hospitality management [Chang et al., 2016], health services [Oliver, 2011], public governance [Mols et al., 2014], and, broadly, in the economics of individual choices [Sunstein, C. and Reisch, L. (eds.), 2017]. In this essay, we explore this notion to see if by actively providing greater levels of reduced packaged laundry detergents, retailers could influence the sales of such products relative to the non-reduced packaged alternatives.[1]

The rest of the paper is organized as follows. In Section 3.2, we review the relevant literature and develop a theoretical framework. In Section 3.3, we describe our methodology and the data used. In Section 3.4, we provide empirical results. In Section 3.5, we conclude the paper.

3.2 Theoretical Framework and Hypothesis Development

Consistent with existing theoretical and empirical studies, we expect that there are two primary mechanisms that retailers can take to have an impact on sales of reduced packaged goods. In the first one, individual firms that have sizable market power can make decisions that may have market-wide effects. For instance, conditional on characteristics of consumer goods, early research has shown that retailers can create systems in which they have substantial market power over manufacturers [Porter, 1974, Meza and Sudhir, 2010].

Consequently, in the context where Walmart sets preferences on detergent package sizes [Walmart, 2007, 2008], a requirement for reduced packaged goods from this retailer is likely to act as an important change factor in the detergent industry. There exists empirical evidence that access to this giant retailer's shelves or its insistence on certain concessions with manufacturers has a direct and significant impact on

[1]Related to this, adopting reduced packaged laundry detergents may help drive down the numbers of potentially serious pollution offenders. It is estimated that 700 million empty laundry detergent jugs are annually discarded into US landfills [McFarland, 2016]. Reducing water content through product concentration can directly diminish the package size, thus significantly benefiting retailers, manufacturers, and the environment. For example, Puracy Natural laundry detergent is concentrated to such extent that the potency of a 24-ounce bottle of the product is equivalent to that of a 144-ounce non-concentrated Arm and Hammer detergent. Given the weight difference of almost six times, in this extreme example, a retailer would be better off in terms of shelf space utilization by stocking more of Puracy Natural-sized detergents than almost any other detergent size.

manufacturers' bottom line and behavior [Bloom and Perry, 2001, Spicer and Hyatt, 2017]. Specifically, Bloom and Perry [2001] show that manufacturers with larger shelf space in Walmart stores can command greater sales than their competitors, though those with limited shelf access are better off elsewhere. An overall assessment of Walmart's push for environmentally-friendly packaging is documented in detail by Spicer and Hyatt [2017], who discuss the incidence of cost savings to both the retailer and manufacturers. Therefore, with regards to retailer market power and product sales, the first formal hypothesis we state is:

Hypothesis 1. *An action toward reduced package detergent by a firm with significant market power will shift market shares of reduced packaged detergents. Stated directly, as Walmart shifts to reduced packaged detergents, the market share (aggregate units sold) of reduced packaged detergents increases.*

In the second mechanism, which we argue applies to a broad spectrum of retailers, one can select a certain share of reduced packaged goods to influence their sales. It has been long established that retail product assortments affect consumer preferences and purchases [Simonson, 1999].

Historically, in the operations literature, the scholars have looked at the problem of product assortment as the tool to predict and satisfy consumer's preferences and tastes [Chong et al., 2001, Cachon and Kok, 2007, Caro and Gallien, 2007]. However, our field is yet to explore the ways of leading, not predicting, the consumer preferences by adopting elements of nudging [Donohue et al., 2019]. Thus, we argue that retailers can exert nudges toward sales of reduced packaged products by offering more reduced packaged choices.

To test this expectation, we seek to utilize information on aggregate product levels and market shares of reduced packaged products to see how a change in ratios of reduced packaged products affects the growth in market shares of reduced packaged products. Market share of frequently purchased, branded consumer goods, is defined as "a convex function of distribution, increasing at an increasing rate up to 100 percent distribution" [Farris et al., 1989, p.107]. This conclusion is based on their observation that instead of a 'diminishing returns' curve at certain levels of product distribution for frequently purchased goods, the trend was convex at higher levels of product distribution in the market.

The operational outcome is shaped by a set of parsimonious expectations that a choice to offer certain new products affects existing consumer choices, which in turn can augment consumer preferences between previously and newly offered products. Such augmentation of consumer product demand patterns will ultimately have an impact on levels of product sales in retail stores. Therefore, we expect that an increase in the ratio of reduced packaged products will lead to a convex growth of market shares of reduced packaged products. Despite the logical parsimony of such a convex expectation, no empirical evidence currently exists on the relationship between a share of reduced packaged detergents and their subsequent levels of sales. To address this gap, we develop and state our second formal hypothesis below:

Hypothesis 2. *Increasing the ratio of reduced packaged products will lead to a convex growth in sales of reduced packaged products. Stated directly, as the ratio of reduced packaged detergent assortment increases, sales (units sold) of reduced packaged detergents increase at a growing rate.*

3.3 Methodology

3.3.1 Data and Measurement

Key variables come from the syndicated retail sales scanner data IRI Marketing Data Set [Bronnenberg et al., 2008]. It contains 11-years of sales information of laundry detergents across more than 1,200 stores in 50 U.S. markets at SKU/store/week level for brands like Tide, Cheer, Gain, Arm & Hammer, Surf, Fab, All, Xtra, and others.

Table 3.1: Brief Market-wide Statistics

Type of Packaging	Total Units	Total Dollars	Total Obs.	Total SKUs
Non-reduced	20,175,360	$104,427,356	2,849,681	1,184
Reduced	11,540,741	$69,165,993	2,122,081	1,288
Total	31,716,101	$173,593,349	4,971,762	2,472

Most brand extensions offer multiple SKUs due to a combination of scents and sizes of that product. For example, Purex's " Unscented 2X Concentrated" detergent is available in three sizes, 100, 80, and 50 oz. As a result, the total number of unique SKUs present in the data set is initially almost 2,500. We remove detergent forms that are unusual or low selling ("ball", "bar", "gel", "missing", "packet", "plastic", "pouch", "powder pods", and "sheets"), and only focus on detergents that are sold in liquid form (a total of 4,971,774 obs.). Since concentrated detergent allows the removal of pure water from the detergent formula, which in turn makes the effective product volume smaller but still as potent as its non-concentrated counterparts, we let the concentration level associated with each particular detergent to be the proxy for package reduction. Detergents that are labeled as either "classic" or "non-concentrated" are identified as "non-reduced packaged". Detergents that are labeled as either "2x", "concentrated", "ultra-concentrated", "3x", "4x", "6x", "8x", "ultra-concentrated", and so on are identified as "reduced packaged".

Table 1 provides a more detailed breakdown of analyzed data by type of packaging–reduced and non-reduced packaged products. Non-reduced packaged products sold a total of 20,175,360 units, whereas reduced packaged ones sold 11,540,741 units. Dollarswise, the numbers are $104,427,356 and $69,165,993, respectively. A total count of 2,849,681 observations is associated with non-reduced packaged-good purchases, whereas for reduced packaged good purchases, the number of observations is 2,122,081. Finally, a total of 1,184 distinct SKUs are present in the data set, with 200 SKUs having non-reduced packaging and 1,288 SKUs with reduced packaging.

3.3.2 Estimation

We evaluate hypothesis one by generating an aggregate weekly time series data set. To estimate whether Walmart's announcement with regards to reduced packaged goods had a market-wide implication, we adopt a set of interrupted time-series analyses. An interrupted time-series solution is suitable for this test because the dependent variable of interest is observed over equidistant weekly intervals before and after retailer intervention. The intervention by Walmart with regards to reduced packaged detergents, if significant, is predicted to shift the sales trend of reduced packaged detergents market-wide. Existing econometric research shows that such designs have substantial internal validity in quasi-experimental designs, when pre- and post-intervention trends are evaluated Shadish et al. [2002], Campbell and Stanley [1966].

Generally, here are two key approaches to interrupted time-series models that can accommodate estimations with autocorrelated data. Linden (2015) shows that an interrupted time-series analysis for a single group can be estimated with Newey-West standard errors to handle autocorrelation and possible heteroskedasticity, as well as the generalized least-squares approach that assumes the errors are from an AR(1) process. In the context of Walmart's announcement and its impact on the share of reduced market products in the market, Equation (3.1) is such that:

$$\text{Market Share}_t = \beta_0 + \beta_1 \text{T}_t + \beta_2 \text{Announcement}_t + \beta_3 \text{Announcement}_t T_t + e_t \tag{3.1}$$

The dependent variable is **Total weekly market share** of reduced packaged products, represented below in Equation (3.2). An intercept β_0 is the predicted level of market share of reduced packaged detergents in the beginning of the time period under evaluation. Coefficient β_1 is the slope of reduced packaged detergents before Walmart's announcement during T_t time of the study. The announcement Announcement_t, or intervention itself is an identification variable equal to 1 after the intervention and zero otherwise, with a coefficient of β_2. Finally, β_3 is the slope after the announcement, which is an interaction term between time and intervention.

$$\text{Market Share}_t = \frac{\text{Reduced Packaged Units}_t}{\text{Total Units}_t} \tag{3.2}$$

Table 3.2: Description of Variables

Variable	Description
Hypothesis 1:	
Market Share$_t$	ratio of reduced packaged units$_t$ over total units$_t$
Reduced Packaged Units$_t$	reduced package units sold in week t for $t = 1, 2..., W$
Total Units$_t$	total units sold in week t for $t = 1, 2..., W$
Announcement$_t$	official Walmart press release indicator in week t
T_t	week indicator for week t for $t = 1, 2..., W$
Hypothesis 2:	
$UnitMarketShare_{it}$	ratio of reduced package units sold over total units sold at store i for $i = 1, 2, \ldots, I$ in week t for $t = 1, 2..., W$
$Fraction_{it}$	ratio of reduced packaged SKU count over total SKU count at store i for $i = 1, 2, \ldots, I$ in week $t$for $t = 1, 2..., W$
Average Non-Reduced Package Price$_{it}$	Average cents per ounce for non-reduced packaged products at store i for $i = 1, 2, \ldots, I$ in week t for $t = 1, 2..., W$
Average Reduced Package Price$_{it}$	Average cents per ounce for reduced packaged products at store i for $i = 1, 2, \ldots, I$ in week t for $t = 1, 2..., W$

For robustness purposes of the findings to variances in regional contexts, we re-estimated interrupted time-series equations for each of the nine regions in the sample. The regions are East-North Central, East-South Central, Mid-Atlantic, Mountain, New England, Pacific, South Atlantic, West-North Central, and West-South Central.

In order to test for hypothesis two, we construct a number of new measures by aggregating observations at the store/week level (after the aggregation, the final count of observations is 134,743). The panel regression model at the store/week level is expressed in Equation 3.3.

$$\begin{aligned}\text{LnUnitMarketShare}_{it} &= \beta_0 + \beta_1 \text{LnFraction}_{it} + \beta_2 \text{LnFraction}_{it}^2 \\ &+ \beta_3 \text{Average Non-Reduced Package Price}_{it} \\ &+ \beta_4 \text{Average Reduced Package Price}_{it} \\ &+ \beta_5 \text{Store}_{it} + \beta_6 \text{Week}_{it} + e_{it} \qquad (3.3)\end{aligned}$$

where $UnitMarketShare_{it}$ is a percentage of all reduced packaged product units sold at store/week level defined in Equation (3.4). An intercept β_0 in the fixed effects model is the level of unit market shares when all else is held at zero. $Fraction_{it}$ is a percentage of reduced packaged products over an entire product assortment at the store/week level defined in Equation (3.5). For example, if 10 out of 50 units sold were that of reduced package SKUs, then the market share is 20%. If 10 out of 20 SKUs sold were reduced packaged products, then the fraction is 50%.

$$UnitMarketShare_{it} = \frac{\text{Reduced package units sold}_{it}}{\text{Total units sold}_{it}} \qquad (3.4)$$

$$Fraction_{it} = \frac{\text{Reduced package SKU count}_{it}}{\text{Total SKU count}_{it}} \qquad (3.5)$$

To operate with a meaningful range of unit market shares of reduced package products, we focus on the period of time when the percent of reduced packaged products was yet to be fully saturated with such products, i.e. the percent of reduced packaged products was nearly or at 100%. Hence, we focus on the time period up to the point when this percent has reached 99%. This happened approximately a year after Walmart's announcement in 2007 (about 50 weeks after). This is done to omit the time period when the market sold nothing but reduced packaged products. The same operation is completed for the fraction measure. To capture the potential non-linearity of the relationship, we introduce a quadratic term for $Fraction_{it}$. Consequently, coefficients β_1 and β_2 are non-linear effects of fraction on the unit share of reduced packaged detergents.

Furthermore, at the store-week panel level, we add price control measures to ensure proper model specification. Higher average cents per ounce for non-reduced packaged goods is likely to work in favor of unit market shares of reduced packaged goods, while higher average cents per ounce for reduced packaged goods would work in the opposite direction. Coefficients β_3 and β_4 represent their effects. A detailed description of variables is in Table 3.2. Summary statistics are provided in Table 3.3.

Table 3.3: Descriptive Statistics of Numerical Variables

Variable	**Median**	**Mean**	**Std. dev**	**Min**	**Max**
Unit Market Share	16.67	26.43	25.83	0.039	99.89
Fraction Reduced Packaged	20.00	28.75	21.01	0	100
Av. cents per ounce non-reduced	5.08	5.19	1.75	0.008	89.93
Av. cents per ounce reduced	9.56	9.61	5.15	0.02	99.50

As the time series and panel models show signs of autocorrelation, we keep in mind the change in the value of the ratio variable over time for each store. In these data sets, at about week 405 from the beginning of the first time period in the sample, market ratio approaches the value of 1, exhibiting little to no trend variation after week 405. Therefore, we focus on the first 405 weeks of the time series and panel distributions to test for hypotheses 1 & 2.

3.4 Empirical analysis

There are two primary sets of interrupted time-series models. The first one is a model with Newey-West standard errors with zero lags, which, while correcting for heteroskedasticity, does not account for potential autocorrelated errors. This model is not properly specified because the Breusch-Godfrey postestimation test shows clear evidence of autocorrelation in the time-series data sets. Serial autocorrelation remains significant all the way to a 42nd lag, but the partial autocorrelations decay after a third lag. Therefore, the second model is based on a Newey-West standard errors with three lags. As postestimation regression statistics show, the best fit is offered in Model 2, which is a model with Newey-West standard errors correcting for both heteroskedastic and autocorrelated errors.[2] An alternative model variety is the interrupted time-series model with Prais correction, which assumes that the errors are from an AR(1) process. This model, Model 3 here, however, is significantly weaker than the Newey-West corrected model with lagged effects in Model 2. The results for interrupted time series regressions are presented in Table 3.4.

The aggregate time-series distribution of the market share of reduced packaged goods indeed shows a significant shift in their unit sales at about week 351 reaching 100 percent of market share at about week 405. This is depicted in Figure 3.1 as dashed, darker lines. The market share of non-reduced packaged goods, however, has a symmetrically reversed trend. This is shown in Figure 3.1 as dotted, lighter lines. The trend is consistent in all nine regional markets included in the data set.

Empirical results from the interrupted time series regressions offer significant and substantive support in favor of Hypothesis 1. Figure 3.2 contains observed and fitted regression lines from Model 2, where one can observe an almost perfect fit. The slope for time, while statistically significant, is substantively rather small–evidence that the growth of sales for reduced packaged detergents prior to Walmart's announcement was slow. The significant coefficient for the announcement from Walmart, or intervention, separates the market shares of reduced packaged products to pre- and post-announcement periods. While the increase in market shares of reduced packaged goods before week 351 was slow, the slope shifts upwards by an angle of about 75 degrees after the intervention. Within approximately 50 weeks (about a year), the market consisted exclusively of concentrated detergents. Therefore, there is no

[2]The use of other lags, such as 1 or 2 lags or up to 42 lags, does not offer better fit than a model with 3 lags.

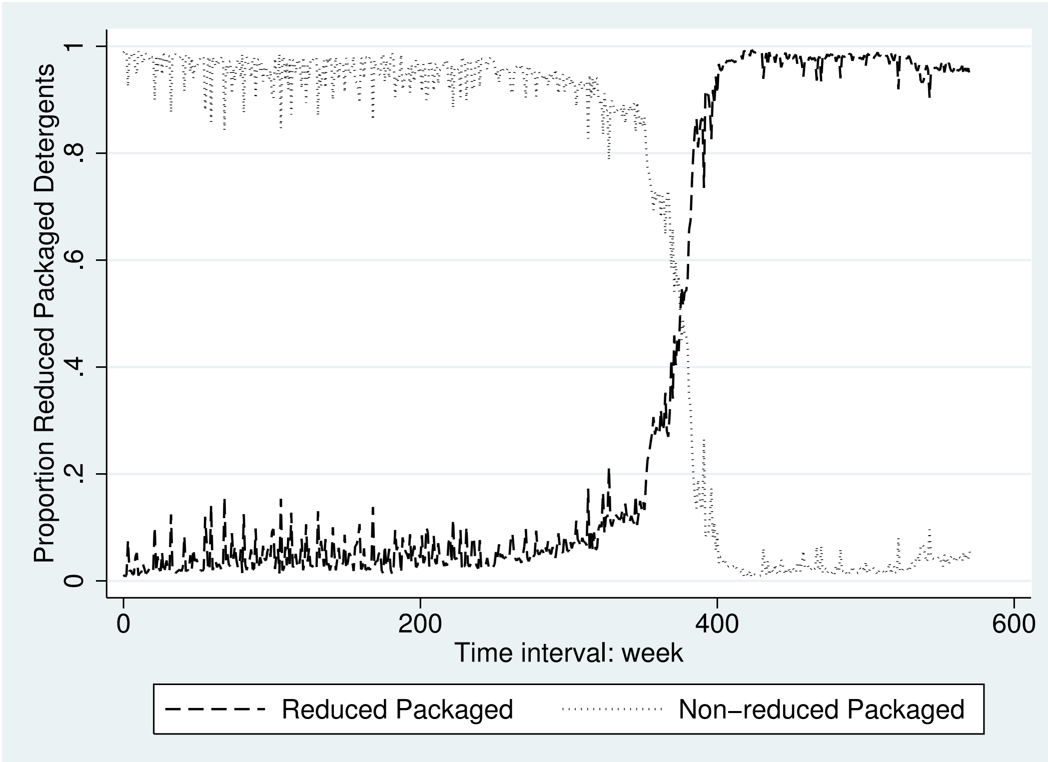

Figure 3.1: Aggregate Market Share of Reduced Packaged Detergent

doubt that the retailer's intervention resulted in an industry-wide shift toward reduced packaged detergents.

Table 3.4: Empirical Results for Interrupted Time-Series Models

	Model 1 (lag 0 Newey-West)	Model 2 (lag 3 Newey-West)	Model 3 Prais AR(1))
Intercept	0.023*** (7.04)	0.023*** (7.02)	0.022*** (3.78)
Time	0.000*** (10.17)	0.000*** (8.91)	0.000*** (6.50)
Announcement	0.057*** (3.94)	0.058** (3.01)	0.053** (2.98)
Time x Announcement	0.016*** (36.08)	0.016*** (27.66)	0.016*** (29.53)
N	410	410	410
Adj. R-sq	0.7434	0.9916	0.9332
t-statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			

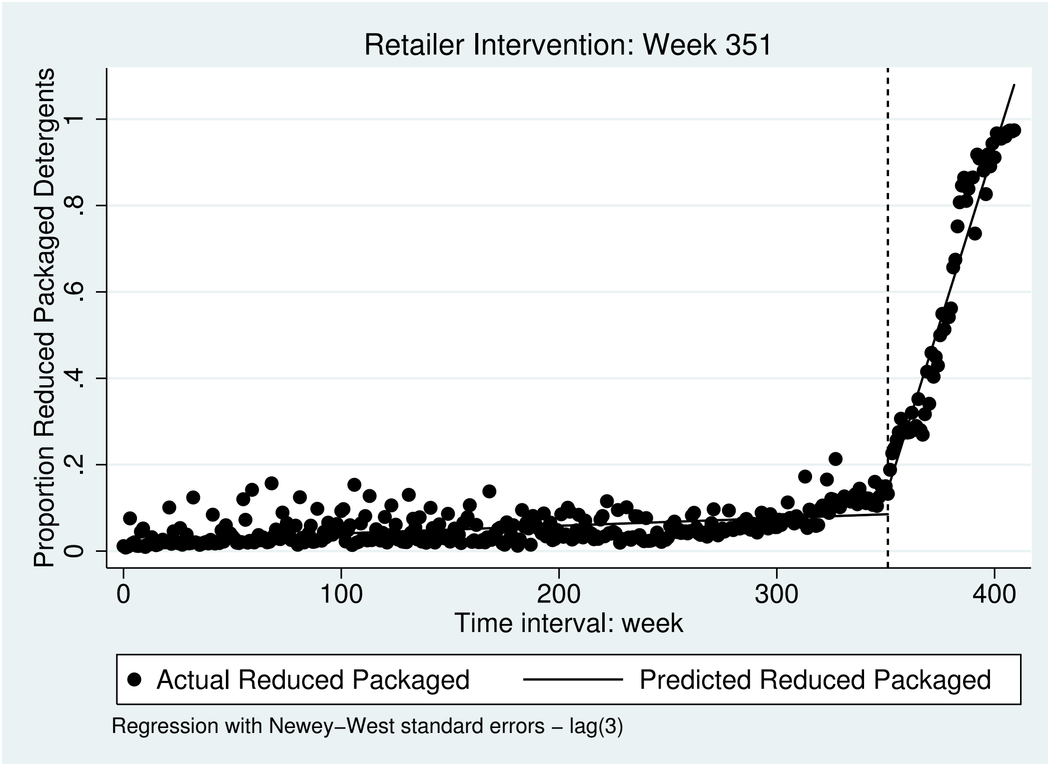

Figure 3.2: Interrupted Time-Series Regression Model Fit.

Region-based interrupted time series models show a slight variation between the regional markets, with East-South Central, Mountain, and West-South Central regions experiencing an almost instantaneous switch to reduced packaged detergent products. Overall, the intervention's impact, which is represented in the steepness of the change angle due to Walmart's announcement, ranges from about 0.70 degrees to almost 0.85 degrees. These change angles can be seen in the figures of fitted interrupted time-series regression models for each region (Appendix 3.5 and 3.5).

In the fixed effects panel regression models (see results in Table 3.5), which are estimated with standard errors corrected for heteroskedasticity, as well as lagged effects for the outcome of interest, coefficients for fraction and it's quadratic term are significant and positive.[3]

[3]Since the Hausman test shows that fixed effects models should be preferred, which is indicative of underlying store-week effects, the results for random effects models

All else equal, the log-log coefficient varies between 0.870 and 0.973 in Models 4 and 5, respectively. Therefore, a one percent increase in the fraction of reduced packaged goods results in 0.87 percent to 0.973 increase in units sold for reduced packaged products. The coefficient for the quadratic term is equal to 0.0499 and 0.0317 in Models 4 and 5. Consequently, there is evidence that the relationship between the fraction of reduced packaged products and the units sold of reduced packaged products is non-linear. Thus, the retailer can work on the upper end of the ratio of reduced packaged products spectrum to have a convex influence on the market shares of reduced packaged goods. These results offer evidence in support of Hypothesis 2. Control variables are statistically significant and consistent with expected directions of the relationship. Higher prices for non-reduced packaged detergent products have a positive association with units sold of reduced packaged detergents, while the relationship is negative when the prices for reduced packaged detergent products are higher.

Table 3.5: Empirical Results for Panel Fixed Effects Models

	Model 4 Panel FE	Model 5 Panel FE with lagged Y_{it}
Intercept	-0.660*** (-11.11)	-0.945*** (-10.30)
L1.Y_{it}	—	0.0340*** (10.25)
ln(Fraction)	0.870*** (25.48)	0.973*** (19.78)
ln(Fraction) Squared	0.0499*** (9.96)	0.0317*** (4.34)
Av. cents per ounce non-reduced	0.0784*** (18.80)	0.103*** (14.14)
Av. cents per ounce reduced	-0.0264*** (-27.66)	-0.0316*** (-26.54)
N (obs)	146,397	65,277
N (groups)	2,702	2,295
Adj. R-sq (within)	0.4863	0.5288
Adj. R-sq (between)	0.7423	0.6939
Adj. R-sq (overall)	0.5301	0.5622
t-statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

are not discussed for brevity or statistical necessity. For example the Hausman test for Model 4 and its random effects equivalent has $\chi^2 = 192.20$ and P-value < 0.001.

We also estimated region-based fixed effects regressions for the relationship between the ratio of reduced packaged detergents and their sales. Overall, these additional results continue to offer statistically significant support in favor of hypothesis 2. These results are presented in the appendix section. The coefficient for the ratio ranges between 0.509 in the West-South Central region to 1.156 in New England. The convexity coefficient is significant in all but one region–New England, ranging between 0.0298 in the East-North Central region to 0.108 in the West-North Central region. Considering that New England has the highest coefficient for the ratio of reduced packaged detergents measure, this is not substantively important. Conclusions with regards to control measures for prices of non-reduced and reduced packaged detergents, respectively, continue to hold.

3.5 Conclusion

Changes toward concentrated products are becoming ubiquitous. Concentrated soups, concentrated juices, concentrated coffee brews, or concentrated dish-washing liquids can now be found at any grocery store. Concentrated content due to diminishing levels of water use can lower the amount of pure water added in the product and can make the final products more compact in size. The study we present here discusses and empirically tests levers that retailers can exert to shape the sales of reduced packaged consumer products and have a significant impact on the market share of such goods. Broadly speaking, empirical results lend significant evidence to our hypotheses that large retailers, such as Walmart, can be instrumental in shifting toward reduced packaged products in the market, while ordinary retailers can actively manage their ratios of reduced package products to see accelerated growth in sales of reduced package products. This is consistent with extant research on market power (Porter, 1974) and on the convex nature of the relationship between product supply and aggregate levels of product sales (Farris et al., 1989).

The study offers practical implications to research on levers available to retailers. The first finding that a large retailer can have an industry-wide power is relevant to both retail actors and manufacturers (and, perhaps, regulators). Furthermore, a choice to offer certain products as a nudging exercise affects existing sales. In practical terms, retailers are capable of actively managing their supply of reduced package goods, but they should be mindful of a convex nature of products sales as a function of such retail choices. Product manufacturers would also be keenly interested in knowing that selecting reduced packaging solutions does not impact adversely their cost-benefit bottom-line, provided that retailers commit to mitigating known problems from potentially low visibility concerns.

There are several limitations in the study which necessitate that the application of empirical findings to practice be conducted with caution. First, we work with retail transactions data that inherently omit smaller stores. Caution must be exercised when generalizing our findings to such stores. Second, we work with detergent products, which can be considered an essential good that almost every household requires. The results may vary for products that are exclusive or in geographic locations dominated by certain types of retail consumers or non-household consumers (commercial, tourist areas, dominant consumer preferences for “green” products, or even areas with sparse populations). We encourage future research to tackle “these” limitations.

Chapter 4 Conclusion

Essays in this dissertation evaluate retailer optimization and efficiency techniques using grocery store scanner data. In the first essay, we show that optimizing product selection for promotional display space is an important lever that grocery store managers have at their disposal to influence customers' purchasing decisions and increase the profitability of their stores. In this study, we provide a decision support tool for choosing which SKUs to place on special promotional display spaces (such as end-of-aisle displays) inside a grocery store. Our methodology allows a retailer to choose a SKU for each promotional display space that results in the largest improvement in incremental profit for that particular store location.

Historically, retailers have identified which SKUs to put on promotional display spaces using simple heuristics, such as picking a best-selling SKU or the same SKU that was assigned on display during that time period the previous year. Our methodology offers several improvements over these existing practices. Our methodology proposes an estimation technique for measuring the incremental lift in sales of placing a particular SKU on promotional display space. These incremental lifts (represented by estimates of the percent increase in sales) are estimated using a sample from a national grocery store sales transaction dataset (collected by IRI), which allows us to estimate the sales lifts from a much larger set of SKUs than if the estimates were made using only the transaction data from a single store or store chain. This allows us to even estimate the sales lift for SKUs that have never been put on promotional display at a particular retailer.

Our estimation methodology is capable of handling an extensive and complex product assortment and captures important aspects of promotional activities such as cannibalization of the inner aisle sales and halo effects. Our methodology also includes an optimization model for selecting which SKUs to put on promotional display for each individual store. The optimization model includes the incremental lifts (from the estimation method) combined with the estimated base-sales rates and profit margins of each SKU so that the profit-maximizing SKU can be chosen for a promotional display space for each week of the year. Our optimization model is also flexible enough to consider several practical aspects such as common business rules that restrict the selection of the same SKU over a consecutive set of weeks, display-related changeover costs, and trade fund deals, which can provide grocers with additional profit through agreements with manufacturers concerning the placement of the manufacturers' products on promotional displays.

Our study identifies several opportunities for future research. We have focused on the selection of SKUs to be placed on a promotional displays assuming that product categories have already been assigned to displays. An empirical example of such an extension will require the use of market basket data, which we did not possess. Another future research opportunity would be to develop an estimation model that would capture the decay of the display lift over time. As with many types of promotions, the lift from a display promotion can diminish over time if the display continues to have the same item. A model that incorporates the decay of the display lift would identify when to switch a promotional display to a new SKU so that a store manager does not have to rely on specific business rules to make such a decision.

In the second essay, we argue that current business tendencies toward a smaller store format among grocery retailers make it more difficult for a store or chain manager to determine the most essential product assortment to carry due to tighter space limitations and the current proliferation of products with various attributes. We offer a systematic, data-driven methodology to empirically identify attribute-based product demand structures, also known as decision trees, that can help to narrow down a large attribute-based pool of products to a most essential subset a store manager needs to carry. Our methodology carefully identifies the importance of product attributes and accounts for attribute-based substitution across products.

Using a large sample of beer sales across the US, we identified that the costumers first care about the brand information when they seek to purchase beer. They first look at the brand information of the beer. Once the brand is chosen, each brand has a unique path toward the final choice of a product. In our empirical demonstration of the five top-selling brands Bud Light, Budweiser, Budweiser Select, Coors Light, and Miller Lite, the decision tree creates a path toward identifying the final five products out of a total of 53 that belong to these five brands. We show that brands don't tend to have identical tree branches, meaning that consumers set attribute priorities differently for each brand. Hence, for a retail store manager this information must serve as a guide when determining which products to retain in the assortment.

Finally, in the third essay, we present and empirically test levers that retailers can exert to shape the sales of reduced packaged consumer products and have a significant impact on the market share of such goods. Broadly speaking, empirical results lend significant evidence to our hypotheses that large retailers, such as Walmart, can be instrumental in shifting toward reduced packaged products in the market, while ordinary retailers can actively manage their ratios of reduced package products to see accelerated growth in sales of reduced package products.

The study offers practical implications to research on levers available to retailers. The first finding that a large retailer can have an industry-wide power is relevant to both retail actors and manufacturers (and, perhaps, regulators). Furthermore, a choice to offer certain products as a nudging exercise affects existing sales. In practical terms, retailers are capable of actively managing their supply of reduced package goods, but they should be mindful of a convex nature of products sales as a function of such retail choices. Product manufacturers would also be keenly interested in knowing that selecting reduced packaging solutions does not impact adversely their cost-benefit bottom-line, provided that retailers commit to mitigating known problems from potentially low visibility concerns.

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Bibliography

N. Agrawal and S. Smith. Optimal retail assortments for substitutable items purchased in sets. *Naval Research Logistics*, 50(7):793–822, 2003.

K. Ailawadi, B. Harlam, J. Cesar, and D. Trounce. Retailer promotion profitability: The role of promotion, brand, category, and market characteristics. *Journal of Marketing Research*, 43(4):518–535, 2006.

K. Ailawadi, K. Gedenk, C. Lutzky, and Neslin. S. Decomposition of the sales impact of promotion-induced stockpiling. *Journal of Marketing Research*, 44(3):460–467, 2007.

G. Allenby. A unified approach to identifying, estimating and testing demand structures with aggregate scanner data. *Marketing Science*, 8(3):265–280, 1989.

Amazon.com, Inc. Form 10-K 2018 Filing. `https://www.sec.gov/Archives/edgar/data/1018724/000101872418000005/amzn-20171231x10k.htm`, 2018.

M. Anders. 4 ways your grocery store may change in 2018. `https://www.forbes.com/sites/melissaanders/2017/12/29/4-grocery-store-trends-to-watch-in-2018/#d31b44748ef9`, 2017. Online; accessed October 10, 2018.

E. Anderson and H. Amato. A mathematical model for simultaneously determining the optimal brand-collection and display-area allocation. *Operations Research*, 22(1):13–21, 1974.

K. Arnold. Publix plans next-gen, delivery-focused store in longwood. `http://www.orlandosentinel.com/business/consumer/os-bz-publix-longwood-delivery-20180129-story.html`, 2018. Access date August 26, 2018.

L. Baardman, M. Cohen, K. Panchamgam, G. Perakis, and D. Segev. Scheduling promotion vehicles to boost profits. *Forthcoming in Management Science*, 2018. `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2638396`.

J. Bayer, M. Hilding, A. Kamps, G. Sahlen, and R. Sparrefors. When product complexity hurts true profitability. `http://www.accenture.com`, 2013. Accessed date December 10, 2017.

D. Bell, D. Corsten, and G. Knox. Unplanned category purchase incidence: Who does it, how often, and why. working paper. Philadelphia: Wharton School, University of Pennsylvania., 2009.

G. Berbeglia, A. Garassino, and G. Vulcano. A comparative empirical study of discrete choice models in retail operations. Working Paper, 2018.

S. Berry. Estimating discrete-choice models of product differentiation. *Rand Journal of Economics,*, 25(2):242–262, 1994.

BevSpot, Inc. How beer, wine, and liquor sales trend by season (2017 edition). `https://www.bevspot.com/2017/08/09/how-beer-wine-and-liquor-sales-trend-by-season-2017-edition/`, 2017. Accessed date December 10, 2017.

R. Bezawada, S. Balachander, P. Kannan, and V. Shankar. Cross-category effects of aisle and display placements: a spatial modeling approach and insights. *Journal of Marketing*, 73(3):99–177, 2009.

A. Bhattarai. Will the rapidly shrinking store save retail? The Washington Post. December 25, 2017, 2017. Online; accessed April 2018.

J. Blackhurst, T. Wu, and P. O'Grady. PCDM: a decision support modeling methodology for supply chain, product and process design decisions. *Journal of Operations Management*, 23(3-4):325–343, 2005.

R. Blattberg and S Neslin. *Sales promotion: Concepts, methods and strategies.* Prentice-Hall, Englewood Cliffs, NJ, 1990.

R. Blattberg and K. Wisniewski. How retail price promotions work: Empirical results. Working paper 43. Chicago: University of Chicago, 1987.

R. Blattberg, R. Briesch, and E. Fox. How promotions work. *Marketing Science*, 14(3): G122–G132, 1995.

P. Bloom and V. Perry. Retailer power and supplier welfare: The case of wal-mart. *Journal of Retailing,*, 77(2):379–396, 2001.

P. Boada-Collado and V. Martínez-de-Albéniz. Estimating and optimizing the impact of inventory on consumer choices in a fashion retail setting. Working paper, 2014.

P. Boatwright and J. Nunes. Reducing assortment: An attribute-based approach. *Journal of Marketing*, 65(3):50–63, 2001.

N. Borin, P. Farris, and J. Freeland. A model for determining retail product category assortment and shelf space allocation. *Decision Sciences*, 25(3):359–384, 1994.

P. Breuer, L. Forina, and J. Molton. Beyond the hype: Capturing value from big data and advanced analytics. perspectives on retail and consumer goods., 2013. Online; accessed July 2016.

Brewers Association. The timing of craft sales. `https://www.brewersassociation.org/insights/timing-of-craft-sales/`, 2014. Accessed date December 10, 2017.

S. Broniarczyk, W. Hoyer, and L. McAllister. Consumer perceptions of the assortment offered in a grocery category: The impact of item reduction. *Journal of Marketing Research*, 35(2):166–176, 1998.

B. Bronnenberg, M. Kruger, and C. Mela. The IRI marketing data set. *Marketing Science*, 27(4):745–748, 2008.

K. Burchell, R. Rettie, and K. Patel. Marketing social norms: Social marketing and the 'social norm approach'. *Journal of Consumer Behavior*, 12(1):1–9, 2012.

G. Cachon and G. Kok. Category management and coordination in retail assortment planning in the presence of basket shopping consumers. *Management Science*, 53(6):934–951, 2007.

G. Cachon, C. Terwiesch, and Y. Xu. Retail assortment planning in the presence of consumer search. *Manufacturing & Service Operations Management*, 7(4):330–346, 2005.

D. Campbell and J. Stanley. *Experimental and Quasi-Experimental Designs for Research*. Chicago, IL: Rand McNally, 1966.

K. Campo, E. Gijsbrechts, and P. Nisol. Dynamics in consumer response to product unavailability: do stock-out reactions signal response to permanent assortment reductions? *Journal of Business Research*, 57(8):834–843, 2004.

P. Carbonara. Walmart, Amazon Top World's Largest Retail Companies. `https://www.forbes.com/sites/petercarbonara/2018/06/06/worlds-largest-retail-companies-2018/#40ca3adb13e6`, 2018.

F. Caro and J. Gallien. Dynamic assortment with demand learning for seasonal consumer goods. *Management Science*, 53(2):276–292, 2007.

L. Catchpole. What is nudging, and how can it boost sales? `https://www.retailsector.co.uk/40377-what-is-nudging-and-how-can-it-boost-sales/`, 2018. Online; accessed August 2019.

O. Cetin, A. Mersereau, and A. Parlakturk. Management and effects of in-store promotional displays. *Manufacturing and Service Operations Management*, Forthcoming, 2018.

H. Chang, C. Huh, and M. Lee. Would an energy conservation nudge in hotels encourage hotel guests to conserve? *Cornell Hospitality Quarterly*, 57(2):172–183, 2016.

P. Chintagunta, V. Kadiyali, and N. Vilcassim. Endogeneity and simultaneity in competitive pricing and advertising: A logit demand analysis. Working paper. Ithaca: Johnson Graduate School of Management, Cornell University, 1999.

J. Chong, T. Ho, and C. Tang. A modeling framework for category assortment planning. *Manufacturing & Service Operations Management*, 3(3):191–210, 2001.

Code of Federal Regulations. Misbranding for Reasons Other Than Labeling, 2018. 21 CFR 100-100.

M. Cohen, N. Leung, K. Panchamgam, G. Perakis, and A. Smith. The impact of linear optimization on promotion planning. *Operations Research*, 65(2):446–468, 2017.

P. Corbett. Purex laundry detergent to cut its water content by 25 percent. https://www.azcentral.com/story/money/business/2014/05/13/purex-laundry-detergent-cut-water-content-percent/9049081/, 2014. Online; accessed April 2018.

E. Crowe. The changing face of convenience. https://www.specialtyfood.com/news/article/changing-face-convenience/, 2015. Access date August 26, 2018.

I. Currim, R. Meyer, and N. Le. Disaggregate tree-structured modeling of consumer choice data. *Journal of Marketing Research*, 25(August):253–65, 1988.

J. Davis, G. Gallego, and H. Topaloglu. Assortment optimization under variants of the nested logit model. *Operations Research*, 62(2):250–273, 2014.

J. Dawes. Brand-pack size cannibalization arising from temporary price promotions. *Journal of Retailing*, 88(2):343–355, 2012.

G. S. Day, Shocker A. D., and R.K. Srivastava. Customer-orientated approaches to identifying product markets. *Journal of Marketing*, 43(4):8–19, 1979.

W. DeSarbo and G. De Soete. On the use of hierarchical clustering for the analysis of nonsymmetric proximities. *Journal of Consumer Research*, 11(1):601–610, 1984.

A. Diaz. A sperm whale that washed up on a beach in spain had 64 pounds of plastic and waste in its stomach. cnn. https://www.cnn.com/2018/04/11/health/sperm-whale-plastic-waste-trnd/index.html, 2018. Article.

K. Donohue, O. Ozer, and Y. Zheng. Behavioral operations: Past, present, and future. *M&SOM*, forthcoming, 2019.

X. Dreze, S. Hoch, and M. Purk. Shelf management and space elasticity. *Journal of Retailing*, 70(4):301–326, 1994.

N. Duan. Smearing estimate: A nonparametric retransformation method. *Journal of American Statistical Association*, 78(383):605–610, 1983.

W. Elmaghraby and P. Keskinocak. Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science*, 49(10):1287 – 1309, 2003.

EPA. Advancing sustainable materials management: Facts and figures. tables 10, 25. `https://www.epa.gov/sites/production/files/2016-11/documents/2014_smm_tablesfigures_508.pdf`, 2016. Online; accessed April 2017.

M. Eriksen, L. Lebreton, H. Carson, M. Thiel, C. Moore, J. Borerro, F. Galgani, P. Ryan, and J. Reisser. Plastic pollution in the world's oceans: More than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea. *PLoS ONE*, 9(12):1–15, 2014.

Euromonitor. Laundry Care in the US. Report, 2018. Online; accessed April 2018,.

P. Farris, J. Olver, and C. de Kluyver. The relationship between distribution and market share. *Marketing Science*, 8(2):107–128, 1989.

J. Feldman and H. Topaloglu. Capacity constraints across nests in assortment optimization under the nested logit model. *Operations Research*, 63(4):812–822, 2015.

M. Fisher and R. Vaidyanathan. A demand estimation procedure for retail assortment optimization with results from implementations. *Management Science*, 60(10):2401–2415, 2014.

A. Flores, G. Berbeglia, and P. Van Hentenryck. Assortment optimization under the sequential multinomial logit model. Working Paper, 2018.

E. Foekens, P. Leeflang, and D. Wittink. A comparison and an exploration of the forecasting accuracy of a nonlinear model at different levels of aggregation. *International Journal of Forecasting*, 10(2):245–61, 1994.

D. Fok, P. Franses, and R. Paap. Seasonality and non-linear price effects in scanner-data-based market-response models. *Journal of Econometrics*, 138(1):231–251, 2007.

E. Fox, A. Montgomery, and L. Lodish. Consumer shopping and spending across retail formats. *Journal of Business*, 77(2):25–60, 2004.

S. France and S. Ghose. An analysis and visualization methodology for identifying and testing market structure. *Marketing Science*, 35(1):182–197, 2016.

D. Frazier. Revolutionary in-store insights: Endcap displays and the shopper. `http://www.catman.global`. Accessed April 15, 2019, 2014.

M. Friedl and C. Brodley. Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, 61(3):399–409, 1997.

G. Gallego and H. Topaloglu. Constrained assortment optimization for the nested logit model. *Management Science*, 60(10):2583–2601, 2014.

G. Gallego and R. Wang. Multiproduct price optimization and competition under the nested logit model with product-differentiated price sensitivities. *Operations Research*, 62(2):450–461, 2014.

A. Garrido-Morgado and A. Gonzalez-Benito. Merchandising at the point of sale: differential effect of end of aisle and islands. *BRQ Business Research Quarterly*, 18(1):57–67, 2015.

V. Gaur and D. Honhon. Assortment planning and inventory decisions under a locational choice model. *Management Science*, 52(10):1528–1543, 2006.

K. Gedenk, K. Neslin, and K. Ailawadi. *Retailing in the 21st Century*, chapter Sales Promotion, pages 345–359. Springer Verlag Publishers, 2006.

R. Geyer, J. Jambeck, and K. Law. Production, use, and fate of all plastics ever made. *Science Advances*, 3(7), 2017.

T. Goldsby and R. Martichenko. *Lean Six Sigma Logistics: Strategic Development to Operational Success*. J. Ross Publishing, 2005.

J. Gong, M. Smith, and R. Telang. Substitution or Promotion? The Impact of Price Discounts on Cross-Channel Sales of Digital Movies. *Journal of Retailing*, 91(2):343–357, 2015.

R. Grover and W. Dillon. A probabilistic mod- el for testing hypothesized hierarchical market structures. *Marketing Science*, 4(4):312–335, 1985.

R. Grover and V. Srinivasan. A simultaneous approach to market segmentation and market structuring. *Journal of Marketing Research*, 24(2):139–153, 1987.

K. Gustafson. Target is chasing wal-mart with its smaller stores but using a different playbook. `https://www.cnbc.com/2016/10/05/`

target-is-chasing-wal-mart-with-its-smaller-stores-but-using-a-different-playbook.html, 2015. Access date August 26, 2018.

D. Hall. Throwaway culture has spread packaging waste worldwide. Waste packaging. https://www.theguardian.com/environment/2017/mar/13/waste-plastic-food-packaging-recycling-throwaway-culture-dave-hall, 2017.

B. Hardie, L. Lodish, P. Fader, A. Sutcliffe, and W. Kirk. Attribute-based market share models: Methodological development and managerial applications. Working paper. London: London Business School, 1998.

J. Hausman, G. Leonard, and J. D. Zona. Competitive analysis with differentiated products. *Annales de Economie et de Statistique*, 34:159–180, 1994.

D. Hellstrom. *Consequences of introducing an innovative unit load carrier in a retail supply chain. In On interactions between Packaging and Logistics - Exploring implications of technological developments Division of Packaging Logistics.* Lund University, 2007.

A. Hubner and K. Schaal. An integrated assortment and shelf-space optimization model with demand substitution and space-elasticity effects. *European Journal of Operational Research*, 261(1):302–316, 2017.

K.-L. Hui. Product variety under brand influence: An empirical investigation of personal computer demand. *Management Science*, 50(5):686âĂŞ700, 2004.

J. Inman and R. Winer. Where the rubber meets the road: A model of in-store consumer decision making. *Number Tech. Rep., Marketing Science Institute, Cambridge, MA*, pages 98–122, 1998.

K. Johnson. Grocery store tour: Shopping the perimeter. https://mayoclinichealthsystem.org/hometown-health/speaking-of-health/grocery-store-tour-shopping-the-perimeter, 2018. Accessed April 15, 2019.

J. Kacen, J. Hess, and D. Walker. Spontaneous selection: the influence of product and retailing factors on consumer impulse purchases. *Journal of Retailing and Consumer Services*, 19(6):578–588, 2012.

D. Kahneman and A. Tversky. Prospect theory: An analysis of decision under risk,. *Econometrica*, 47(2):263–291, 1979.

W. Kamakura, B. Kim, and J. Lee. Modeling preference and structural heterogeneity in consumer choice. *Marketing Science*, 15(2):152–172, 1996.

P. Kannan and S. Sanchez. Competitive market structures: A subset selection analysis. *Management Science*, 40(11):1484–1499, 1994.

P.K. Kannan and G.P. Wright. Modeling and testing structured markets: A nested logit approach. *Marketing Science*, 10(1):58–82, 1991.

S. Kapner. Wal-mart puts the squeeze on food costs. {http://archive.fortune.com/2008/05/28/magazines/fortune/kapner_walmart.fortune/index.htm}, note = Online; accessed April 2017,, 2008.

M. Ketzenberg, R. Metters, and V. Vargas. Inventory policy for dense retail stores. *Journal of Operations Management*, 18(3):303–316, 2000.

A. Kok and Y Xu. Optimal and competitive assortments with endogenous pricing under hierarchical choice models. *Management Science*, 57(9):1546âĂŞ1563, 2010.

G. Kok and M. Fisher. Demand estimation and assortment optimization under substitution: Methodology and application. *Operations Research*, 55(6):1001–1021, 2007.

G. Kok, M. Fisher, and R. Vaidyanathan. *Assortment Planning: Review of Literature and Industry Practice*. In Retail Supply Chain Management, Agrawal N. and Smith S. A., Eds. Springer Science+Business Media New York, 2015.

D. Kollat and R. Willett. Customer impulse purchasing behavior. *Journal of Marketing Research*, pages 21–31, 1967.

J. Larson, E. Bradlow, and P. Fader. An exploratory look at supermarket shopping paths. *International Journal of Research in Marketing*, 22(4):395–414, 2005.

L. Leuthesser, C. Kohli, and K. Harich. Brand equity: the halo effect measure. *European Journal of Marketing*, 29(4):57–66, 1995.

M. Levy and B. Weitz. *Retailing Management, 5th ed*. Boston: McGraw- Hill, 2004.

G. Li and P. Rusmevichientong. A greedy algorithm for the two-level nested logit model. *Operations Research Letters*, 42(5):319âĂŞ324, 2014.

Y. Li and G.J. Tellis. Does province matter? intra-country differences in the takeoff of new products. *Technovation*, 2015.

H. Lindh. Sustainable packaging of organic food: Myth or reality? Doctoral dissertation. Lund University, Lund, Sweden, 2016.

S. Ma and R. Fildes. A retail store sku promotions optimization model for category multi-period profit maximization. *European Journal of Operations Research*, 260(2):680–692, 2017.

S. Mahajan and G. van Ryzin. Stocking retail assortments under dynamic consumer substitution. *Operations Research*, 49(3):334–351, 2001a.

S. Mahajan and G. van Ryzin. Inventory competition under dynamic consumer choice. *Operations Research*, 49(5):646–657, 2001b.

S. Makridakis. Accuracy measures: theoretical and practical concerns. *International Journal of Forecasting*, 9(4):527–529, 1993.

M. Mazerolle. Improving data analysis in herpetology: using akaikeâĂŹs information criterion (aic) to assess the strength of biological hypotheses. *Amphibia-Reptilia*, 27: 169âĂŞ180, 2006.

D. McFadden, A. Bemmaor, F. Caro, F. Dominitz, B.-H. Jun, A. Lewbel, R. Matzkin, F. Molinari, N. Schwarz, R. Willis, and J. Winter. Statistical analysis of choice experiments and surveys. *Marketing Letters*, 16(3-4):183âĂŞ96, 2005.

M. McFarland. Why laundry detergent caps are stuck in the past. `https://www.washingtonpost.com/news/innovations/wp/2016/03/29/why-laundry-detergent-caps-are-stuck-in-the-past/?noredirect=on&utm_term=.6de354bb7136`, 2016. Online; accessed April 2018.

S. McIntyre and C. Miller. The selection and pricing of retail assortments: an empirical approach. *Journal of Retailing*, 75(3):295–318, 1999.

C. Mela, S. Gupta, and D. Lehmann. The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. *Journal of Marketing Research*, 34(2):248–261, 1997.

N. Meyersohn. How a cheap, brutally efficient grocery chain is upending america's supermarkets. `https://www.cnn.com/interactive/2019/05/business/aldi-walmart-low-food-prices/index.html`, 2019. Access date August 26, 2018.

S. Meza and K. Sudhir. Do private labels increase retailer bargaining power?,. *Quantitative Marketing and Economics,*, 8(3):333–363, 2010.

F. Mols, A. Haslam, J. Jetten, and N. Steffens. Why a nudge is not enough: A social identity critique of governance by stealth. *European Journal of Political Research*, 54 (1):81–98, 2014.

A. Montgomery. Creating micro-marketing pricing strategies using supermarket scanner data. *Marketing Science*, 16(4):315–337, 1997.

R. Nakamura, M. Suhrcke, R. Pechey, M. Morciano, M. Roland, and T. Marteau. Impact on alcohol purchasing of a ban on multi-buy promotions: a quasi-experimental evaluation comparing scotland with england and wales. *Addiction*, 109(4):558–67, 2014.

R. Narasimhan, S. Talluri, J. Sarkis, and A. Ross. Efficient service location design in government services: a decision support system framework. *Journal of Operations Management*, 23(2):163–178, 2005.

M. Natter, T. Reutterer, A. Mild, and A. Taudes. Practice prize report – an assortment wide decision-support system for dynamic pricing and promotion planning in diy retailing. *Marketing Science*, 26(4):576–583, 2007.

S. Neslin. *Sales Promotion*. Cambridge MA: Marketing Science Institute, 2002.

V. Nijs, M. Dekimpe, J. Steenkamp, and D. Hanssens. The category-demand effects of price promotions. *Marketing Science*, 20(1):1–22, 2001.

T. Novak. Log-linear trees: Models of market structure in brand switching data. *Journal of Marketing Research*, 30(3):267–287, 1993.

A. Oliver. Is nudge an effective public health strategy to tackle obesity? yes. *The BMJ*, 342:d2168, 2011.

P. Patel and J. Jayaram. The antecedents and consequences of product variety in new ventures: An empirical study. *Journal of Operations Management*, 32(1-2):34–50, 2014.

H. Phillips and R. Bradshaw. How customers actually shop: customer interaction with the point of sale. *The Journal of the Market Research Society*, 35(1):51–62, 1993.

J. Pisani. Lighter load: Laundry detergents shrink for Amazon. `https://www.apnews.com/64759004d2ef4c309cadc615581d5782`, 2018.

M. Porter. Consumer behavior, retailer power and market performance in consumer goods industries. *The Review of Economics and Statistics,*, 56(4):419–436, 1974.

P.G. Prendergast and L Pitt. Packaging, marketing, logistics and the environment: are there trade-offs. *International Journal of Physical Distribution and Logistics Management,*, 26(6):60–72, 1996.

J. Raju. The effect of price promotions on variability in product category sales. *Marketing Science*, 11(3):207–220, 1992.

V. Ramaswamy and W. DeSarbo. A new methodology for deriving and analyzing hierarchical product-market structures from panel data. *Journal of Marketing Research*, 27 (4):418–427, 1990.

V. R. Rao and D. J.* Savabala. Inference of hierarchical choice processes from panel data. *Journal of Consumer Research*, 8(1):85–96, 1981.

Reuters. Kellogg testing new cereal box that cuts packaging. {http://www.reuters.com/article/kellogg-box-idUSN2630786920090126}, note = Online; accessed April 2017,, 2009.

E. Robinson Jr. and M. Swink. A comparative model of facility network design methodologies. *Journal of Operations Management*, 13(3):169–181, 1995.

R. Rooderkerk, H. van Heerde, and T. Bijmolt. Incorporating context effects into a choice model. *Journal of Marketing Reseach*, 48(4):767–780, 2011.

R. Rooderkerk, H. van Heerde, and T. Bijmolt. Optimizing retail assortments. *Marketing Science*, 32(5):699–715, 2013.

G. Ruddick. Why are so many retailers gloomy about the bad weather? http://www.telegraph.co.uk/finance/comment/9959867/Why-are-so-many-retailers-gloomy-about-the-bad-weather.html, 2013. Accessed date December 10, 2017.

Rebecca Rupp. Surviving the sneaky psychology of supermarkets. https://www.nationalgeographic.com/people-and-culture/food/the-plate/2015/06/15/surviving-the-sneaky-psychology-of-supermarkets/, 2015. National Geographic.

P. Rusmevichientong, Z. Shen, and D. Shmoys. Dynamic assortment optimization with a multinomial logit choice model and capacity constraint. *International Journal of Forecasting*, 58(6):1666–1680, 2010.

M. Saghir. The concept of packaging logistics. *In: The Second World Conference on POM and 15th Annual POM Conference (submitted for publication)*, 2004.

D. Saure. *Essays in consumer choice driven assortment planning.* PhD dissertation, Columbia University, 2012.

W. Shadish, T. Cook, and D. Campbell. *Experimental and Quasi-Experimental Designs for Generalized Causal Inference.* Boston: Houghton Mifflin, 2002.

A. Shocker, M. Ben-Akiva, B. Boccara, and P. Nedungadi. Consideration set influences on consumer decision-making and choice: Issues, models, and suggestions. *Marketing Letters*, 2(3):181–197, 1991.

Shop Association. A display is a terrible thing to waste. http://www.shopassociation.org/wp-content/uploads/2016/07/POP-Compliance_2016_whitePaper_SM_FINAL.pdf, 2016. report.

I. Simonson. The effect of product assortment on buyer preferences. *Journal of Retailing*, 75(3):347–370, 1999.

M. Sloane. Product visibility on shelves growing concern of makers. {http://articles.sun-sentinel.com/1987-01-02/features/8701010324_1_product-visibility-product-package-supermarket}, note = Online; accessed April 2017,, 1987.

H. Sorensen. The three faces of pathtracker. http://www.shopperscientist.com/2008-10-14.html, 2008. Accessed date December 10, 2017.

A. Spicer and D. Hyatt. Walmart's emergent low-cost sustainable product strategy. *California Management Review*, NA(NA):1–26, 2017.

A. Spring and C. Earl. Waste crisis: Spot the excessive plastic packaging âĂŞ in pictures. https://www.theguardian.com/environment/gallery/2018/jul/08/waste-crisis-spot-the-excessive-plastic-packaging-in-pictures, 2018.

Sunstein, C. and Reisch, L. (eds.). *The Economics of Nudge*, volume 4. London: Routledge. Critical Concepts of Economics, 2017.

Target Brands, Inc. Product placement in retail settings. http://www.google.com/patents/CA2794679A1?cl=en, 2013. USA Patent CA 2794679. Accessed date December 10, 2017.

R. Thaler and C. Sunstein. *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Penguin Books, 2009.

D. Thompson. What in the world is causing the retail meltdown of 2017? https://www.theatlantic.com/business/archive/2017/04/retail-meltdown-of-2017/522384/, 2017. Accessed date October 10, 2018.

K. Train. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press, 2003.

B.. Tuttle. Your grocery store may soon be cut in half. {http://time.com/money/136330/why-your-grocery-store-may-soon-be-cut-in-half/}, note = Online; accessed August 7, 2015,, 2014.

A. Tversky. Elimination by aspects: A theory of choice. *Psychological Review*, 79(4):281–299, 1972.

G. Urban, P. Johnson, and J. Hauser. Testing competitive market structures. *Marketing Science*, 3(2):83–112, 1984.

T. Urban. An inventory-theoretic approach to product assortment and shelf-space allocation. *Journal of Retailing*, 74(1):15–35, 1998.

US Census Bureau. Monthly and annual retail trade. https://www.census.gov/retail/marts/www/adv44510.txt, 2018a. Accessed date July 3, 2018.

US Census Bureau. Estimated monthly sales for retail and food services, by kind of business. https://www.census.gov/retail/marts/www/marts_current.pdf, 2018b. Accessed date October 10, 2018.

S. Van Ewijk and J. Stegemann. Limitations of the waste hierarchy for achieving absolute reductions in material throughput. *Journal of Cleaner Production*, 132:122–128, 2016.

H. van Heerde, P. Leeflang, and D. Wittink. Decomposing the sales promotion bump with store data. *Marketing Science*, 23(3):317–334, 2004.

G. van Ryzin and S. Mahajan. On the relationship between inventory costs and variety benefits in retail assortments. *Management Science*, 45(11):1496–1509, 1999.

Q. Vuong. Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, 57(2):307–333, 1989.

G. Wade. Revolutionary in-store insights: Endcap displays and the shoppe grocery shopper insights (gsi) display deep dive. http://www.cpgcatnet.org/1883612?submenuheader=11, 2014. Accessed date December 10, 2017.

P. Wahba. Why barnes & noble wants smaller stores. fortune magazine. http://fortune.com/2017/11/30/barnes-noble-sales/., 2017. Access date August 26, 2018.

Walmart. Wal-mart to sell only concentrated products in liquid laundry detergent category by may 2008. http://corporate.walmart.com/_news_/news-archive/2007/09/26/wal-mart-to-sell-only-...., 2007. Online; accessed April 2017.

Walmart. Wal-mart completes goal to sell only concentrated liquid laundry detergent. http://corporate.walmart.com/_news_/news-archive/2008/05/29/wal-mart-completes-goal-to-sell-only-concentrated-liquid-laundry-detergent, 2008. Online; accessed April 2017.

X. Wan, P. Evers, and M. Dresner. Too much of a good thing: The impact of product variety on operations and sales performance. *Journal of Operations Management*, 30(4):316–324, 2012.

M. Weinmann, C. Schneider, and J. Brocke. Digital nudging. *Business & Information Systems Engineering*, 58-6:433–436, 2016.

D. Wiener-Bronner. How to solve the world's plastics problem: Bring back the milk man. https://www.cnn.com/interactive/2019/01/business/loop-reusable-packaging-mission-ahead/index.html, 2019. Retrieved February 1, 2019.

D. Wittink, M. Addona, W. Hawkes, and J. Porter. The estimation, validation, and use of promotional effects based on scanner data., 1988. Working paper.

J. Wooldridge. *Econometric Analysis of Cross Section and Panel Data, 2nd Ed.*. The MIT Press, 2010.

C. Ziliani and S. Bellini. Retail micro-marketing strategies and competition. *The International Review of Retail, Distribution and Consumer Research*, 14(1):7–18, 2004.

M. Zogby, T. Patterson, and K. McBeth. Not Edible, But Still Empty: Manufacturers of Non-Food Products are also Targets for Slack Fill Litigation. `https://www.iadclaw.org/`, 2018.

Appendix A. Considerations for Model Development

Cannibalization and/or Category Expansion.

Consumer-driven substitution is an important assumption in many assortment planning models. Given that retailers have fixed store space and financial resources, assortment planning requires a tradeoff between: how many categories retailers carry (called breadth), how many SKUs do they carry in each category (called depth), and how much inventory do they stock of each SKU [Kok et al., 2015]. Thus, the breadth vs. depth tradeoff is a very important strategic decision faced by retailers. If customers have a high propensity to substitute within a particular category, then providing great depth may be less critical than breadth and vice versa. Since the objective of assortment planning models is to determine the best assortment to be carried, then substitution effects naturally need to be factored in and consumer choice models are often used to estimate these effects. Our study, in contrast to the assortment planning literature, focuses on choosing a SKU for promotional display from an existing product portfolio. Thus, capturing the substitution effects between SKUs because of the mere presence of other SKUs is less important in our scenario. This led us to use a log-linear estimation model which provided much faster estimation times, while also being more consistent with current practice.

Once a product assortment has been chosen, price promotions may amplify consumer substitution as consumers often respond to temporary price reductions by switching to the promoted product, thus, cannibalizing the sales of other substitutable non-promoted products. Besides cannibalization of inner aisle sales, price promotions and other types of promotions can result in category expansion. This leads to increased total category sales, not just incremental sales for the promoted product, which can affect overall store profitability [Neslin, 2002]. Thus, promotional activities such as price promotions, promotional display, and other marketing mix activities can result in cannibalization effects and/or category expansion effects. These effects are expected to be stronger for similar items than they are for dissimilar items [Rooderkerk et al., 2011, Tversky, 1972]. To capture these realities associated with promotions, in addition to a SKU's own marketing mix effects, we also account for cross-SKU marketing mix effects, where the cross effects are moderated by the similarities between SKUs.

Weather.

Seasonal variations in grocery store demand can impact beer sales. For instance, the consumption of beer dramatically increases in the summer [Brewers Association, 2014, BevSpot, Inc., 2017]. We control for this seasonality pattern in the consumption of beer [Fok et al., 2007] by including weekly indicators. In addition to seasonality, there is anecdotal evidence that suggests that weather, particularly bad weather, can negatively affect brick-and-mortar retail sales by reducing store traffic. However, we expect a reduction in traffic due to bad weather to be much more significant for stores that sell discretionary items such as apparel, electronics or specialty goods compared to stores that sell grocery items [Ruddick, 2013]. Indeed, the sale of grocery items may actually increase during times of bad weather, due to stockpiling. In addition, since our dataset consists of stores from the same geographic region, the impact of any weather factors should be reasonably constant across the dataset. For these reasons, we do not include any weather effects in our estimation model.

Endogeneity.

In general, a regression between sales and promotional display could result in biased coefficient estimates for promotional display for the following reasons. First, it is reasonable to assume that store managers or retailers do not choose SKUs to put on a promotional display randomly. Second, not controlling for time-invariant omitted factors such as store policies or store manager skills that could affect both sales and promotional display decisions could result in biased estimates. In our data, we find little support for such endogeneity bias. We postulate on this lack of support as follows:

Even though the selection of SKUs to put on promotional display is obviously not random, our data shows that store managers are not in a position to know in advance which SKUs would provide the highest sales lift so that they can choose those SKUs to put on promotional display. The reason is that at a randomly selected store in our dataset, only twelve out of 334 SKUs were placed on promotional display throughout the year, as shown in Table 1.8. Out of those twelve, the vast majority of SKUs – eight – were placed on display only once during the whole year, and four SKUs were each placed four times during the same period. Thus, using the display data for these twelve SKUs is unlikely to be very helpful for a manager of this particular store to know which SKUs provide the largest lift in sales on each week of the year.

But let's assume the decision of what to put on promotional display is being made at the chain level that this store belongs to; thus, we expect the data to reflect this. The data shows that the whole retail chain that the aforementioned store belongs to comprises a total of twelve stores, and only five stores have ever placed beer on promotional display throughout the year. Additionally, at most, only four stores displayed the same SKU simultaneously in the same week, an indication that the decision of what SKUs to put on display was not made at the chain level. For the majority of instances, 55% of the time, a displayed SKU was displayed only at a single store in a particular week in this chain. The scarcity of display decisions at the chain level again shows that it is unlikely for a manager of this retail chain to know which SKUs provide the largest lift in sales in each week of the year.

Alternatively, let's now assume that maybe this specific chain is an exception, so we look at the display activity across stores in the whole New England region. We continue not to find any evidence that the display activity patterns are any different in other New England stores or chains. The New England dataset covers a total of 7 retail chains, with the number of stores ranging from 1 to 32 stores per chain. Across all the store chains, 62% of the time a SKU was displayed only at a single store in the chain for a particular week.

Thus, relying on the limited information on display activity within a store, within a chain, or across multiple chains as shown above, store managers cannot possibly be expected to pick the SKUs that provide the highest sales lift. Even if certain store managers were extremely talented and skillful in terms of picking the best possible SKUs to put on promotional display, these managers are also probably very good at making other decisions that affect sales such as price promotions, advertising, etc. Thus, the relative sales lift of the SKUs selected by these talented store managers will not be inflated or biased upward because the other controls (such as advertising, price promotions etc.) should also have a higher effect on sales. In addition, display decisions are also guided by which products/SKUs are associated with trade promotions at a given time period which introduces an added degree of randomness (at least in terms of estimating sales lifts) to the selection of SKUs that a store manager will choose to put on promotional display, since the manufacturers have many reasons for offering trade-promotions other than just choosing the SKUs with the largest sales lifts. Moreover, we use store-specific effects to control for time-invariant factors such as store manager skills that would drive both sales and promotional display decisions. Finally, we provide some empirical evidence that suggests that store managers do not choose the SKUs that will have the highest sales in the upcoming week on promotional display (either because they cannot anticipate which SKU this will be or they use other criteria to choose a SKU for promotional display). If retailers knew in advance the best possible SKUs, this would suggest that SKUs that exhibit higher sales lifts would be chosen more frequently to be placed on promotional displays. We decided to test whether our data supported this hypothesis. We estimated the sales lifts of placing best-selling SKUs on promotional display (across all stores in New England) and found the correlation between the SKUs' sales lifts and their actual frequency of promotional display within that year to be negative, small, and insignificant (-0.0711). This suggests that retailers are not in a position to anticipate which SKUs will exhibit higher sales lifts when placed on promotional display.

For all the reasons listed above, we believe that this endogeneity bias is mitigated in our setting. We also attempted to statistically test for endogeneity. Since the previous demand estimation literature has only treated promotional display as a control, there is little guidance for what might serve as a good instrument for our problem. Thus, we explored the use of lagged variables given that it is a fairly common approach to create instrumental variables for promotion activities [Neslin, 2002, Chintagunta et al., 1999]. The argument for the inclusion of lagged display (i.e., past display activity) as an instrument is that sales in the current period cannot possibly cause the display of a product in the previous period. We tested different combinations of past display activity as potential instruments but were unable to identify any valid instruments.

Appendix B. The Hierarchical Methodology

Recall that our proposed approach (discussed in the main part of the paper) selects SKUs from different subcategories to evaluate as potential candidates to put on promotional display. After the relative display lift for each SKU is estimated in a single regression, the estimated parameters are used to calculate the incremental profit associated with each SKU. Then the optimization model decides which SKU to assign on a promotional display.

One challenge with this proposed approach is that a product subcategory/category may contain so many different individual SKUs that the regression cannot be estimated in a reasonable amount of time. One solution to this problem is to limit the number of potential SKUs under consideration for promotional display. Of course, this solution may inadvertently leave out the profit-maximizing SKU since it is not known a-priori which SKU is the profit maximizing one. Another option for easing the estimation challenge is to use a Hierarchical approach.

The estimation in the Hierarchical approach is performed separately within each subcategory, which allows a larger number of SKUs to be included in the estimation and optimization steps. Specifically, for each subcategory, it selects a subset of SKUs to evaluate as potential candidates and estimates the relative display lift for each SKU among that subset in a separate regression for each subcategory. Then the estimated parameters from the separate regressions are used to calculate the incremental profit associated with each SKU per subcategory and the optimization model determines which SKU per subcategory maximizes the incremental profit. The final step involves choosing the SKU that maximizes the incremental profit across all subcategories to assign to a promotional display. Since the Hierarchical approach evaluates each subcategory separately, it can consider a much wider selection of SKUs per subcategory than our proposed approach can. This comes at a loss of using across-subcategory variation in sales, however, during the estimation process. Unlike our proposed approach, the Hierarchical approach can only leverage the within-subcategory variation in sales in the estimation.

Neither estimation methodology necessarily dominates the other. The assortment strategy of a retailer should determine which of the two methodologies fits one's business goals best. For small scale stores that only offer a narrow selection of products within a narrow selection of product categories, the originally proposed approach might be more suitable to optimize all the potential display candidates at once. But for large scale retailers that offer a wide selection of products within a wide selection of product categories, the Hierarchical approach might be more preferable as it allows consideration of the widest selection of SKUs within each subcategory for the profit-maximizing display decision.

Next, we briefly discuss the estimation and optimization parts of the Hierarchical methodology.

Sales Response Function

The sales response function for the Hierarchical approach is the same as the model for our proposed approach in (2.1) except that the Subcategory-Week effect is removed, since this method estimates each subcategory $\mathbb{V}_a$ separately. Hence, the number of regressions being estimated equals the number of subcategories considered i.e., C.

Total Incremental Profit

Using the estimates obtained from the sales response function, the incremental profit is determined for each SKU j for each subcategory $\mathbb{V}_a$. For each $\mathbb{V}_a$, we calculate Π_{jti}

as in (1.3), with the exception that the cross-display profits are now calculated per each subcategory, each time assuming that the SKUs in that subcategory are present in the assortment.

Static Optimization

For each store i, week t, and subcategory $\mathbb{V}_a$, we find the best SKU with the highest incremental profit in that subcategory $j_a = \arg\max_{j\in\mathbb{V}_a} \Pi_{jti}$. Finally, once a set of all profit-optimizing SKUs j_a is determined, a global profit-optimizing SKU $j \in \mathbb{V}$ ($j = \arg\max_{j\in\mathbb{V}} \Pi_{jti}$) is selected.

Appendix C. SKU Selection Across Different Product Categories

In this section, we discuss how our methodology can be extended to facilitate the selection of SKUs across different product categories to optimize (incremental) store level profit[4]. The store manager would first need to short-list the product categories that generate significant impulse buying demand and thus, can be good candidates for promotional display. For each product category candidate, a variant of our estimation model, which considers within-category promotional effects in addition to cross-category promotional effects, can be used to estimate each SKU's total incremental profit. (We discuss in this section how our current model can be extended to capture cross-category promotional effects by using an example.) This step would be repeated for every product category candidate. The final step would involve feeding the estimated incremental profits to a variant of our optimization problem to determine the SKUs from different product categories to be placed on promotional display considering the number of available promotional displays and any business rules that the store manager would like to apply.

To determine cross-category promotional effects the store manager would need to know which other product categories would be affected if a SKU from a particular product category was chosen to be placed on promotional display. This requires analysis of basket data, which can be done using readily available commercial software,

[4]This extension of our methodology allows us to select directly SKUs across different categories for promotional display as opposed to selecting first a product category and then the SKU within that product category.

to determine which products are typically purchased together and the strength of their association. Using the results of market basket analysis, the store manager can then identify which product categories need to be evaluated together when making promotional display allocation decisions.

Since we do not possess basket data, we cannot illustrate with actual data how to optimize the promotional display allocation decisions for an entire store. Nevertheless, we describe through an example how our methodology can be extended to select SKUs across different product categories in order to optimize store level profit. Consider an example where the market basket analysis suggests that beer and salty snacks are frequently purchased together and beer is one of the product category candidates for promotional display. To determine which beer SKU should be placed on promotional display, we need to consider the effect of placing each beer SKU candidate on promotional display on (i) its own sales, (ii) the sales of other beer SKUs and (iii) the sales of salty snacks. Recall that our current estimation model given in (2.1) already captures the first two effects. We next develop a model to also account for the third effect i.e., the effect of placing each beer SKU candidate on promotional display on the sales of salty snacks.

We model the demand/sales of a snack SKU $\tilde{j}$ at store i in week t as a log-linear model given in (6). We use the superscripts B and S to denote the variables specific to beer and snack categories respectively. The key variable of interest is the display activity of a beer SKU j (from the consideration set $\mathbb{U}$) in that particular store/week. Specifically, the variable D^{B}_{jti} takes the value of 1 if the beer SKU j was on display in that particular store/week and 0 otherwise. To better isolate the effect of promotional display of beer on salty snacks, we restrict our attention to salty snack sales from the inner-aisles of the stores. We control for other relevant factors that affect the sales of salty snacks such as their price and different marketing-related activities other than promotional display such as discounts, temporary price reductions, advertisements, and coupons. We also include additional controls such as week dummies, snack SKU dummies, store dummies and the interaction term between subcategory and week to control for seasonality, SKU related effects, store fixed effects, and subcategory seasonality respectively.

$$\begin{aligned}\ln S^{\mathrm{S}}_{\tilde{j}ti} \quad = \quad & \overbrace{\delta_0}^{\text{Intercept}} + \overbrace{\sum_{z\in\mathbb{U}} \delta_{1z} Z^{\mathrm{S}}_{\tilde{j}z}}^{\text{SKU Effect}} + \overbrace{\sum_{z\in\mathbb{U}} \delta_{2z}\left(D^{\mathrm{B}}_{jti} Z^{\mathrm{B}}_{jz}\right)}^{\text{Display Effect for Beer}} + \overbrace{\delta_3 H^{\mathrm{S}}_{\tilde{j}ti}}^{\text{\% Discount Effect}} + \overbrace{\delta_4 P^{\mathrm{S}}_{\tilde{j}ti}}^{\text{Price Effect}} \\ & + + \overbrace{\sum_{t'=1}^{T} \delta_{5t'} W_{t't}}^{\text{Week Effect}} \overbrace{\sum_{m\in\mathbb{M}} \delta_{6m} M^{\mathrm{S}}_{\tilde{j}mti}}^{\text{Marketing Mix Effect}} + \overbrace{\sum_{a=1}^{C}\sum_{t'=1}^{T} \delta_{7at'}\left(A^{\mathrm{S}}_{\tilde{j}a} W_{t't}\right)}^{\text{Subcategory-Week Effect}} + \overbrace{\sum_{i'=1}^{I} \delta_{12i'} B_{i'i}}^{\text{Store Effect}} \\ & + \overbrace{e_{\tilde{j}ti}}^{\text{Error Term}}\end{aligned} \tag{6}$$

The estimated parameters (i.e., $\hat{\delta}$s) of (6) are used to calculate the incremental profit generated from the sales of snacks from placing a particular beer SKU on promotional display. The total incremental profit of a beer SKU j including the profit from the snack sales becomes:

$$\Pi_{jti} = \overbrace{q_{jti}(l_{jti}-1)\pi_{jti}\triangle}^{\text{Own-display profit}} + \overbrace{\sum_{j'\neq j} q_{j'ti}(CEL_{jj'i}-1)\pi_{j'ti}\triangle}^{\text{Cross-display profit}} + \overbrace{\sum_{\tilde{j}} q^{\mathrm{S}}_{\tilde{j}ti}(l^{\mathrm{S}}_{\tilde{j}ti}-1)\pi^{\mathrm{S}}_{\tilde{j}ti}\triangle}^{\text{Snack profit}} \tag{7}$$

The base demand $q_{\tilde{j}ti}$ (8) of a snack SKU $\tilde{j}$ is calculated by subtracting from its log-transformed unit sales the estimated effects related to its own-marketing related activities such as feature advertising and price reduction, as well as the effect from putting a beer SKU j on display.

$$\ln\left(q^{\mathrm{S}}_{\tilde{j}ti}\right) \quad = \quad \ln S^{\mathrm{S}}_{\tilde{j}ti} - \sum_{z\in\mathbb{U}} \hat{\delta}_{2z}\left(D^{\mathrm{B}}_{jti} Z^{\mathrm{B}}_{jz}\right) - \hat{\delta}_3 H^{\mathrm{S}}_{\tilde{j}ti} - \sum_{m\in\mathbb{M}} \hat{\delta}_{6m} M^{\mathrm{S}}_{\tilde{j}mti} \tag{8}$$

The SKU-level display lift $l^{\mathrm{S}}_{\tilde{j}ti}$ (9) is also obtained by using the estimates of (6) as follows:

$$\ln\left(l^{\mathrm{S}}_{\tilde{j}ti}\right) = \sum_{z\in\mathbb{U}} \hat{\delta}_{2z}\left(D^{\mathrm{B}}_{jti} Z^{\mathrm{B}}_{jz}\right) \tag{9}$$

Finally, the estimated incremental profits of the beer SKUs become inputs of the optimization problem to determine which beer SKU should be chosen for promotional display over every week in the planning horizon.

In addition to beer sales data, we possess data on the salty snack sales across the same stores in the New England region and the same time period (i.e., year 2011). Our dataset classifies the salty snacks into different types such as potato chips, tortilla/tostada chips, pretzels, cheese snacks, ready-to-eat popcorn, corn snacks, pork rinds, or other salted snacks. Thus, we used the methodology above to test whether placing each of the beer SKUs from our consideration set (see Appendix 3.5 for a full list of these SKUs) on promotional display would have any effect on the sales of all types of salty snacks. We then examined the impact of beer display on each type of salty snack separately. All of the regression models that we ran indicated that the impact of beer display on snack sales was not statistically significant, so we do not report our numerical results here. Despite not finding any statistically significant effects, the same methodology can be applied to other candidate categories that are identified as being frequently sold with beer through the market basket analysis.

Appendix D. Pre-processing

In this section, we discuss an approach that can be used to reduce the scale of the optimization problem. This approach can be extremely useful, especially in situations where a grocer is interested in optimizing the promotional display decisions for an entire store. Given that a typical grocery store carries around 40,000 to 60,000 SKUs, the potential SKU candidates for promotional display can be too large for a mixed-integer optimization solver to handle. We propose an approach that can significantly reduce the number of SKUs that need to be considered in the optimization model while still guaranteeing optimality (i.e., the solution obtained with the restricted number of SKUs is the same as the solution where all SKUs are included in the optimization problem). Our approach assumes that the grocer has already estimated the sales lifts of all SKUs that are potential candidates for promotional display and calculated their corresponding incremental profits.

We next provide an example to motivate our approach. Suppose that a grocery store carries 60,000 SKUs and we are interested in optimizing the promotional display decisions for the entire store. Let's also assume that the number of available displays in a particular week is 10, so that we need 10 SKUs to place on display for the week. For that week, assume that instead of considering all 60,000 SKUs as potential candidates to evaluate and include in the optimization, we sort the SKUs in decreasing order based on their corresponding incremental profits and only select the top 10,000 SKUs to evaluate. Then we should be able to find 10 SKUs out of the 10,000 SKUs to place on display, provided that at least 10 SKUs out of these 10,000 SKUs are "eligible" to be chosen (i.e., placing them on display during this week does not violate any constraints with other SKUs that are already planned for display in the other weeks of the schedule). If this set of 10,000 SKUs is guaranteed to have at least 10 eligible SKUs, then it is unnecessary to consider any other SKUs for display during this week, as any other SKUs will be suboptimal for this week since by definition their incremental profits are below that of the set of 10,000 SKUs. Thus, for this week, we may confine the optimization to select just among these 10,000 SKUs, while guaranteeing that optimality is retained, and thus there is no need to consider all 60,000 SKUs for this week. We can repeat this idea week by week, and in the end of each week, we obtain a set of SKUs to be included in the optimization that is considerably smaller than the 60,000 SKUs.

In this example 10,000 SKUs was large enough to guarantee that we can find the desired number of eligible SKUs to put on display on a given week regardless of their display schedule over some finite time horizon (e.g., a year). We next illustrate how we can obtain an upper bound on the number of SKUs to be considered for optimization on a given week that would always ensure that we can find the required number of desired SKUs to be placed on promotional display that week.

Let's denote by M_t the upper bound[5] on the number of SKUs that are made ineligible to be considered for promotional display in week t due to their display schedule over the other weeks. Recall that k_t is the maximum number of promotional displays available in week t. Once M_t is known, we select the set of SKUs E_t as the top $(M_t + k_t)$ SKUs, ranking in descending order all SKUs for which we have incremental profits by their incremental profit in week t. Note that for the set of SKUs E_t the following always hold:

[5]Here all possible display schedules that meet the constraints of the optimization program proposed in Section 1.3.4 are considered to calculate that upper bound.

- No matter which SKUs are scheduled for promotional display outside of week t, at least k_t SKUs from the set E_t of SKUs remain eligible to be placed for promotional display in week t.
- No optimal solution needs to consider scheduling any other SKUs other than the ones in the set E_t for week t, because by construction it is always better to choose a SKU in E_t, and by the point above one can always find an eligible SKU in E_t.

Recall, that x_{jt} is the decision variable of our optimization model that determines whether SKU j will be chosen for promotional display in week t. Given that in week t it is sufficient to consider just the SKUs in E_t, the total number of decision variables x_{jt} to be included in the optimization becomes

$$\sum_t |E_t|.$$

We next show how to obtain M_t that is the upper bound on the number of SKUs that are made ineligible to be considered for promotional display in week t due to their display schedule over the other weeks. Recall that b_j denotes the maximum number of weeks across the time horizon that SKU j can be placed on promotional display and Q_j denotes the maximum number of weeks in a row that SKU j can be placed on promotional display. We will assume that $b_j = B$ and $Q_j = Q$ for all SKUs[6].

For each week t, the number of items on display is k_t. Thus, the total number of display slots in the entire horizon is

$$K = \sum_t k_t.$$

To identify M_t we need to focus on the constraints that make SKUs ineligible. These constraints are (1.11) and (1.12) of the optimization model in Section 1.3.4.

[6]We can also derive M_t for the case where the b_j are not equal or the Q_j are not equal. However this case is considerably more complicated.

Consider first constraint (1.11) on each SKU j:

$$\sum_{t=1}^{\tilde{T}} x_{jt} \leq B.$$

For this constraint to render a SKU ineligible, the SKU must be scheduled for B weeks, and thus it occupies B of the K slots. Thus, the maximum number of SKUs that can be rendered ineligible by this constraint is

$$\left\lceil \frac{K}{B} \right\rceil.$$

The other constraint which can render SKUs ineligible is constraint (1.12)

$$\sum_{r=0}^{Q} x_{j,t+r} \leq 1$$

which enforces each SKU to be on display at most once within any Q consecutive weeks. For a week t', the maximum number of SKUs rendered ineligible by this constraint is the number of slots that are within distance Q of t and that is

$$\sum_{t=t'-(Q-1)}^{t'+(Q-1)} k_t.$$

This maximum occurs when each of these slots is filled by a different SKU; then none of these SKUs are eligible for week t' since they have already been on display within Q weeks of t'.

Adding together the two separate bounds, we obtain the bound

$$M_{t'} = \left\lceil \frac{K}{B} + K_{t'} \right\rceil$$

where

$$K_{t'} = \sum_{t=t'-(Q-1)}^{t'+(Q-1)} k_t.$$

Suppose we alter constraint (1.12) as follows

$$\sum_{r=0}^{Q} x_{j,t+r} \leq F$$

where $F < Q$, meaning that we allow a SKU to be displayed at most F weeks out of every Q consecutive weeks. Now, for a SKU to be rendered ineligible by this constraint, it must be on display F weeks within distance Q of week t', and thus it occupies F display slots. Hence, the maximum number of ineligible SKUs is

$$\left\lceil \frac{K_{t'}}{F} \right\rceil,$$

giving

$$M_{t'} = \left\lceil \frac{K}{B} + \frac{K_{t'}}{F} \right\rceil, \tag{10}$$

which is a reduction in M_t compared with the case where $F = 1$.

The above discussion illustrates the close connection between the constraints and obtaining bounds M_t, showing how the constraints in this methodology affect the number of SKUs necessary for optimization.

The bound obtained above can be improved. Constraints (1.11) and (1.12) overlap in that a SKU rendered ineligible by either constraint consumes slots from the total pool of slots K. The discussion above does not account for this joint consumption of slots. Suppose for a given week t', S' denotes the number of SKUs rendered ineligible by constraint (1.12). Each such SKU occupies F slots. Consider all possible display schedules where S' SKUs are rendered ineligible by that constraint. The maximum number of SKUs that can be rendered ineligible in any such schedule by constraint (1.11) is

$$\frac{K - FS'}{B}.$$

Instead of just K/B as in the previous discussion, in the numerator, we subtract from K the slots already consumed by the SKUs rendered ineligible by constraint (1.12). Thus, conditional on having S' SKUs rendered ineligible by constraint (1.12), the maximum number of SKUs rendered ineligible by both constraints is

$$\frac{K - FS'}{B} + S' = \frac{K + (B - F)S'}{B} \tag{11}$$

$$= \frac{K}{B} + \frac{B-F}{B} S' \tag{12}$$

We can obtain a bound for $M_{t'}$ by choosing S' that maximizes the above quantity. From the above discussion, we have:

$$S' \leq \frac{K_{t'}}{F}$$

and thus (12) is maximized when equality holds, giving the following value for $M_{t'}$:

$$M_{t'} = \left\lceil \frac{K}{B} + \frac{B-F}{B} \frac{K_{t'}}{F} \right\rceil \tag{13}$$

$$= \left\lceil \frac{K}{B} + \left(\frac{1}{F} - \frac{1}{B} \right) K_{t'} \right\rceil \tag{14}$$

$$= \left\lceil \frac{K - K_{t'}}{B} + \frac{K_{t'}}{F} \right\rceil \tag{15}$$

We may assume $F < B$, since if $F \geq B$ then constraint (1.12) is redundant (and if $F = B$, then the above value for $M_{t'}$ reduces just to K/B, as it should since constraint (1.12) becomes irrelevant and the bound comes only from constraint (1.11)). Hence, $(B-F)/B < 1$, and thus the above bound is smaller than (10). The tradeoff between B and F is shown in (15).

Appendix E. A Complete List of Candidate SKUs to be Considered for Promotional Display with the Static and Dynamic Approach

Name				Units
Amstel Light	Light	Bottle	12-pack	11,048
Bass Pale Ale	Regular	Bottle	12-pack	16,285
Becks	Regular	Bottle	12-pack	14,264
Blue Moon Belgian White Ale	Regular	Bottle	12-pack	21,808
Blue Moon Seasonal Collection	Regular	Bottle	12-pack	10,336
Blue Moon Variety Pack	Regular	Bottle	12-pack	6,535
Bud Light	Light	Can	18-pack	70,950
Bud Light	Light	Can	24-pack	6,898
Bud Light	Light	Bottle	18-pack	53,158
Bud Light	Light	Bottle	24-pack	9,612
Bud Light Lime	Light	Bottle	12-pack	17,400
Budweiser	Regular	Can	18-pack	48,687
Budweiser	Regular	Can	24-pack	5,086
Budweiser	Regular	Bottle	18-pack	25,157
Budweiser	Regular	Bottle	24-pack	5,451
Coors	Regular	Can	18-pack	5,091
Coors Light	Light	Can	18-pack	49,935
Coors Light	Light	Bottle	18-pack	26,396
Corona Extra	Regular	Bottle	12-pack	46,234
Corona Extra	Regular	Bottle	18-pack	9,314
Corona Light	Light	Bottle	12-pack	31,461
Corona Light	Light	Bottle	18-pack	5,560
Dos Equis Xx Lager Especial	Regular	Bottle	12-pack	5,338
Harpoon India Pale Ale	Regular	Bottle	12-pack	18,189
Harpoon Mix Pack	Regular	Bottle	12-pack	5,486
Harpoon Seasonal	Regular	Bottle	12-pack	8,706
Heineken	Regular	Can	12-pack	12,803
Heineken	Regular	Bottle	12-pack	40,833
Heineken Premium Light Lager	Light	Bottle	12-pack	10,914
Landshark Lager	Regular	Bottle	12-pack	7,184

Name				Units
Long Trail Ale	Regular	Bottle	12-pack	16,049
Long Trail Seasonal	Regular	Bottle	12-pack	5,873
Long Trail Survival Variety P	Regular	Bottle	12-pack	11,661
Magic Hat No 9 Ale	Regular	Bottle	12-pack	8,374
Magic Hat Seasonal	Regular	Bottle	12-pack	5,241
Magic Hat Variety Pack	Regular	Bottle	12-pack	12,168
Michelob Light	Light	Bottle	18-pack	11,697
Michelob Light	Light	Can	18-pack	13,358
Michelob Ultra	Regular	Can	18-pack	21,786
Michelob Ultra	Regular	Bottle	18-pack	20,730
Miller Lite	Light	Can	18-pack	37,509
Miller Lite	Light	Bottle	18-pack	21,015
Otter Creek Vermont Sampler	Regular	Bottle	12-pack	5,559
Redhook Long Hammer Ipa	Regular	Bottle	12-pack	7,223
Redhook The Greatest Hits Sam	Regular	Bottle	12-pack	5,456
Samuel Adams Boston Lager	Regular	Bottle	12-pack	36,953
Samuel Adams Light	Light	Bottle	12-pack	15,225
Samuel Adams Seasonal	Regular	Bottle	12-pack	58,836
Samuel Adams Variety Pack	Regular	Bottle	12-pack	32,683
Sea Dog Wild Blueberry Wheat	Regular	Bottle	6-pack	5,487
Shipyard Export Ale	Regular	Bottle	12-pack	5,237
Shipyard Seasonal	Regular	Bottle	6-pack	14,753
Shipyard Seasonal	Regular	Bottle	12-pack	22,822
Shipyard Selection	Regular	Bottle	12-pack	6,798
Shock Top Belgian White Ale	Regular	Bottle	12-pack	11,484
Shock Top Raspberry Wheat Ale	Regular	Bottle	6-pack	5,513
Sierra Nevada Pale Ale	Regular	Bottle	12-pack	10,012
Smuttynose Ipa	Regular	Bottle	12-pack	8,669
Smuttynose Sampler	Regular	Bottle	12-pack	5,828

Appendix F. SKU Selection with Static Approach vs. Benchmark

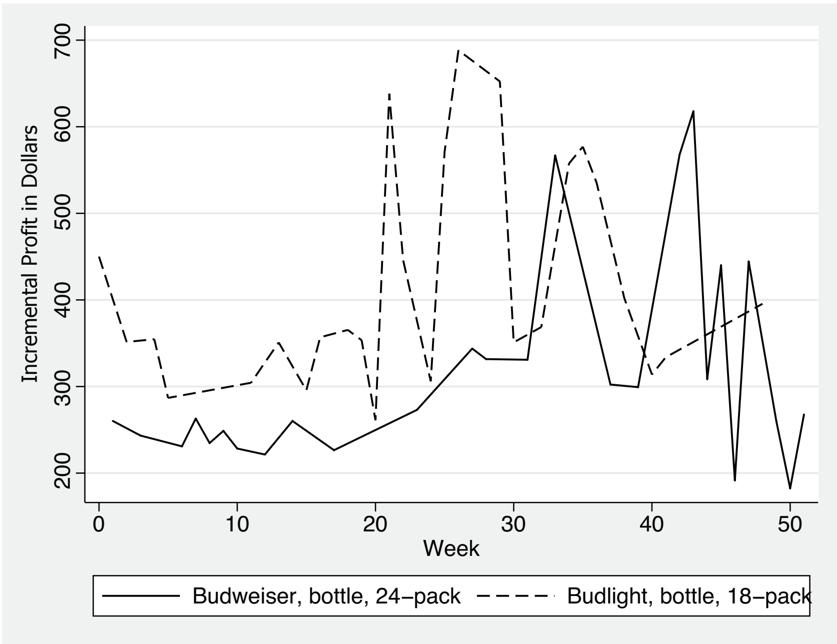

Figure F.1: SKU Chosen with Static Approach and Weekly Incremental Profit

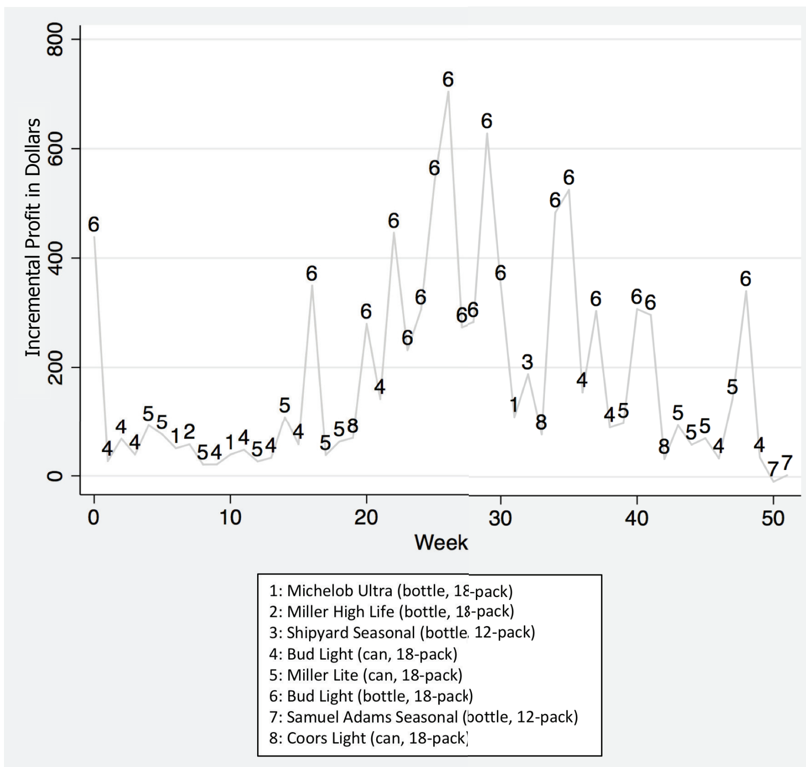

Figure F.2: SKUs Chosen in Benchmark and Weekly Incremental Profit

Appendix G. Interrupted Time-Series Regressions by Region

This subsection presents interrupted time-series regression model fit graphs for each of the nine regions in the data set–East-North Central, East-South Central, Mid-Atlantic, Mountain, New England, Pacific, South Atlantic, West-North Central, and West-South Central.

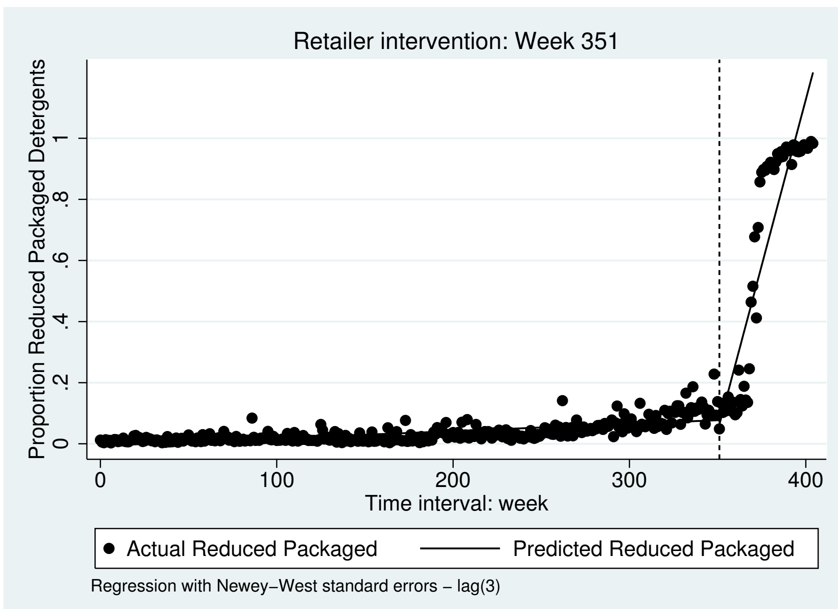

Figure G.1: Interrupted Time-Series Regression Model Fit–East-North Central.

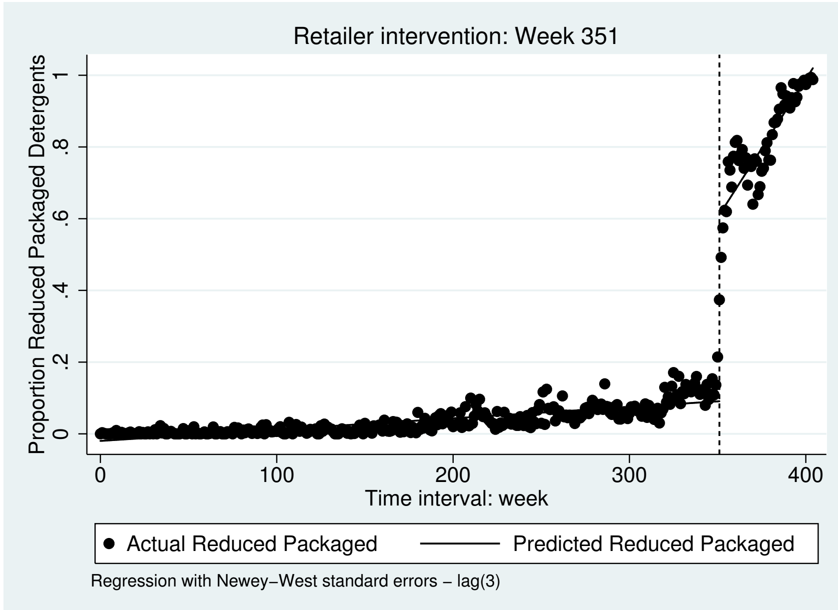

Figure G.2: Interrupted Time-Series Regression Model Fit–East-South Central.

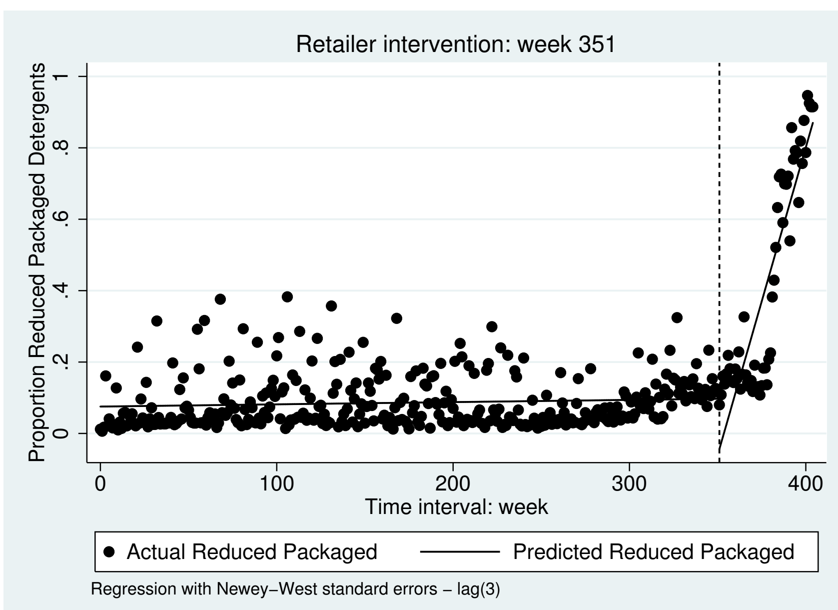

Figure G.3: Interrupted Time-Series Regression Model Fit–Mid-Atlantic.

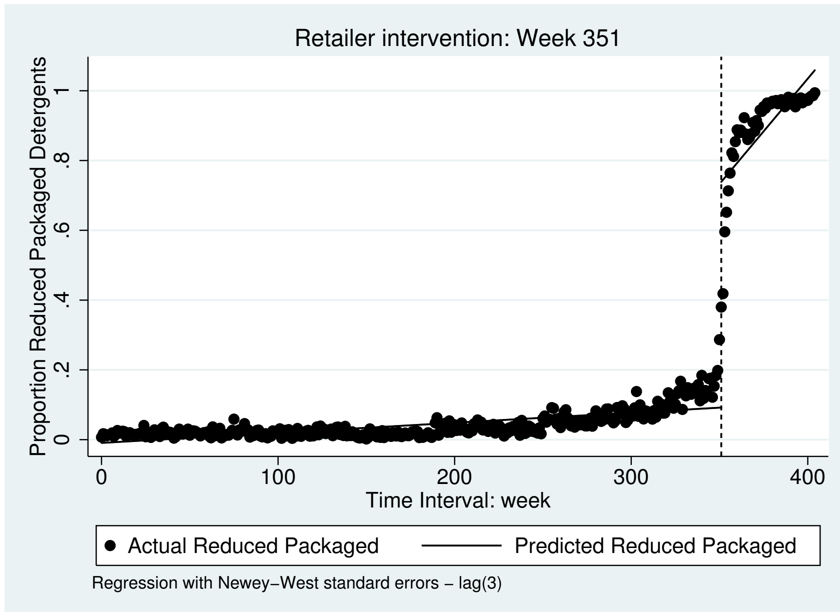

Figure G.4: Interrupted Time-Series Regression Model Fit–Mountain.

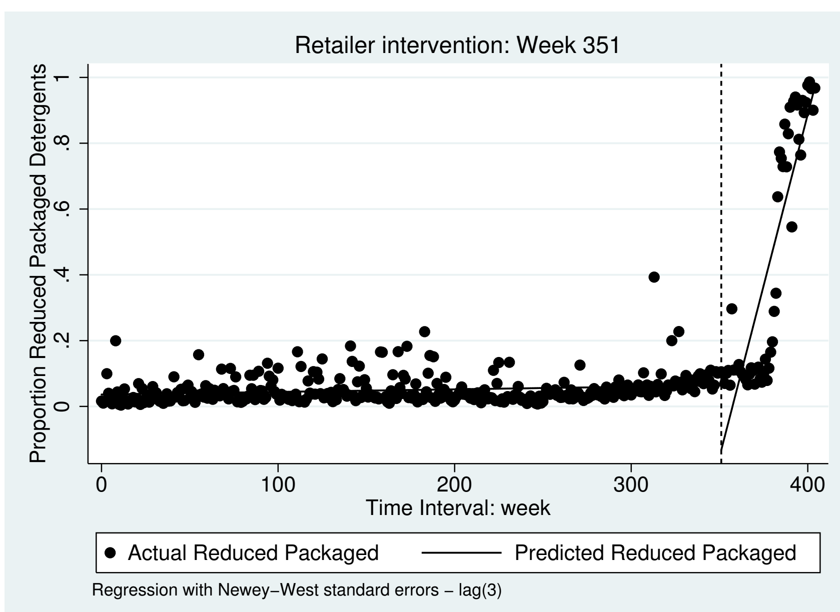

Figure G.5: Interrupted Time-Series Regression Model Fit–New England.

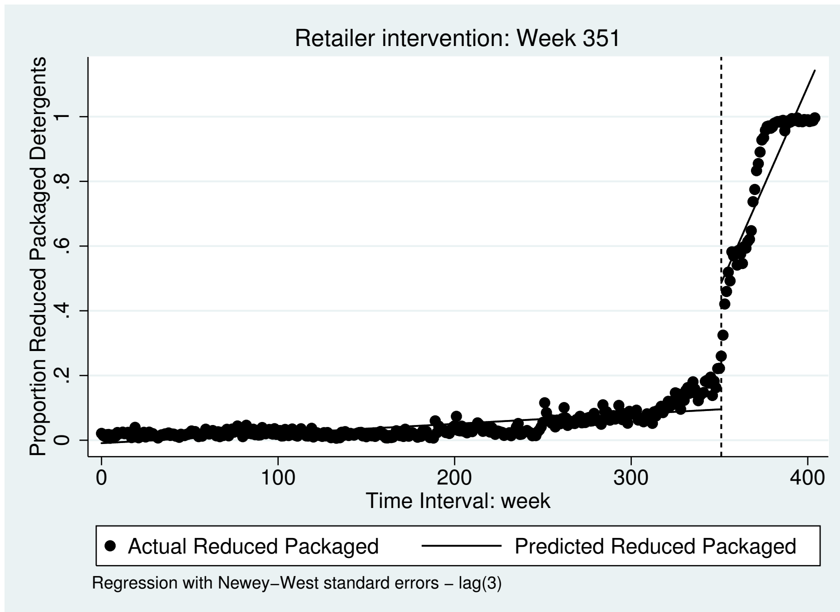

Figure G.6: Interrupted Time-Series Regression Model Fit–Pacific.

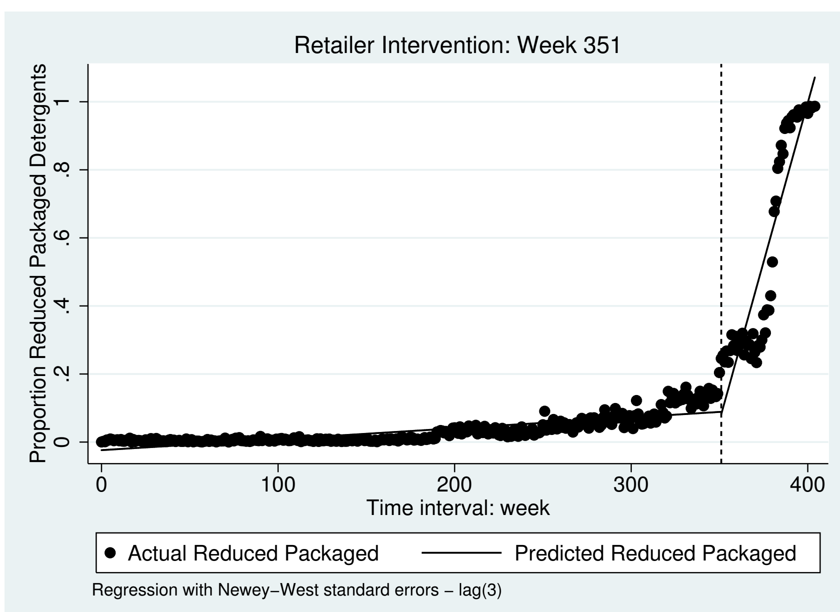

Figure G.7: Interrupted Time-Series Regression Model Fit–South Atlantic.

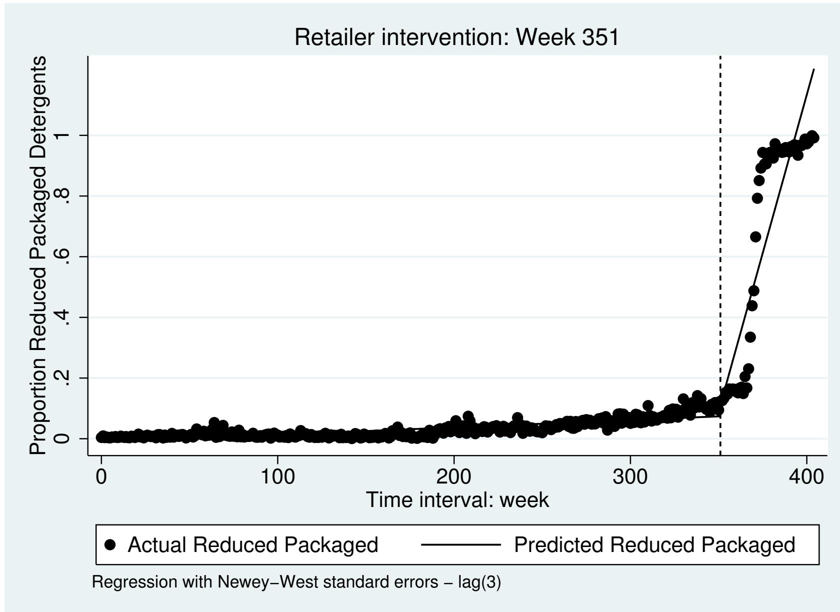

Figure G.8: Interrupted Time-Series Regression Model Fit–West-North Central.

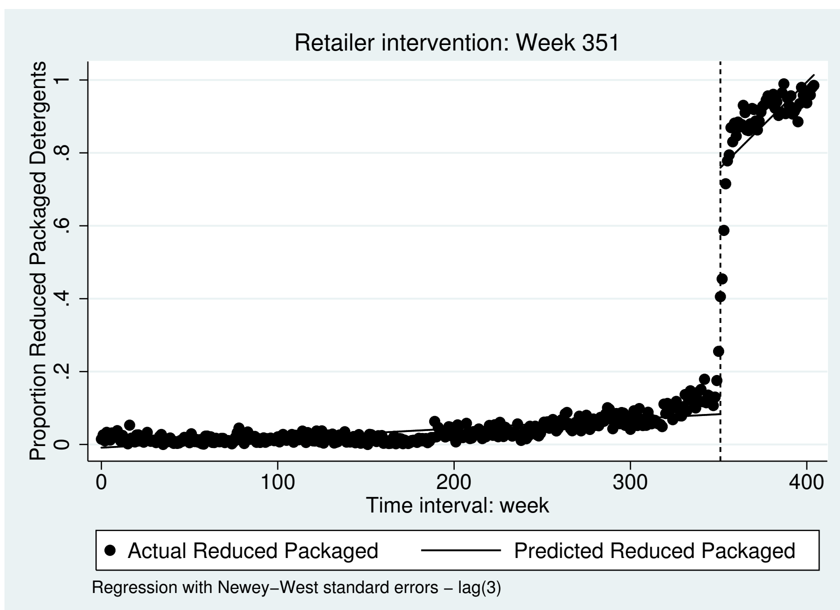

Figure G.9: Interrupted Time-Series Regression Model Fit–West-South Central.

Appendix H. Panel Fixed Effects Regression Results by Region

This subsection presents tables for panel fixed effects regression results for each of the nine regions in the data set–East-North Central, East-South Central, Mid-Atlantic, Mountain, New England, Pacific, South Atlantic, West-North Central, and West-South Central.

Table H.1: Empirical Results for Panel FE by Region—East-North Central, East-South Central, and Mid-Atlantic

1

	Model 6 East -North Central	Model 7 East -South Central	Model 8 Mid -Atlantic
Intercept	-0.985*** (-6.23)	0.232 (0.89)	-0.866*** (-6.86)
ln(Fraction)	1.027*** (11.38)	0.647*** (4.21)	0.692*** (8.48)
ln(Fraction) Squared	0.0298* (2.25)	0.0759*** (3.44)	0.0837*** (6.79)
Av. cents per ounce non-reduced	0.102*** (9.09)	0.0236*** (5.31)	0.166*** (21.63)
Av. cents per ounce reduced	-0.0335*** (-13.34)	-0.0353*** (-7.79)	-0.0369*** (-14.87)
N (obs)	20,480	4,203	37446
N (groups)	393	105	566
Adj. R-sq (within)	0.5190	0.5764	0.4497
Adj. R-sq (between)	0.7188	0.8263	0.7733
Adj. R-sq (overall)	0.5547	0.6020	0.4872
t-statistics in parentheses			
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			

Table H.2: Empirical Results for Panel FE by Region—Mountain, New England, and Pacific

	Model 9 Mountain	Model 10 New England	Model 11 Pacific
Intercept	0.0679 (0.38)	-1.304*** (-9.69)	-0.454** (-3.26)
ln(Fraction)	0.563*** (5.34)	1.156*** (13.50)	0.789*** (9.75)
ln(Fraction) Squared	0.0906*** (6.05)	0.00927 (0.67)	0.0524*** (4.51)
Av. cents per ounce non-reduced	0.0405*** (7.62)	0.102*** (6.23)	0.0731*** (21.60)
Av. cents per ounce reduced	-0.0161*** (-8.54)	-0.0281*** (-10.88)	-0.0144*** (-10.90)
N (obs)	10,098	17,806	23,717
N (groups)	236	235	494
Adj. R-sq (within)	0.5605	0.4383	0.5355
Adj. R-sq (between)	0.8052	0.7391	0.6285
Adj. R-sq (overall)	0.5777	0.4789	0.5505
t-statistics in parentheses			
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			

Table H.3: Empirical Results for Panel FE by Region—South Atlantic, West-North Central, and West-South Central

	Model 12 South Atlantic	Model 13 West -North Central	Model 14 West -South Central
Intercept	-0.0132 (-0.09)	-0.144 (-0.71)	0.207 (0.94)
ln(Fraction)	0.661*** (8.09)	0.519*** (4.38)	0.509*** (3.76)
ln(Fraction) Squared	0.0781*** (6.59)	0.108*** (6.25)	0.0974*** (4.75)
Av. cents per ounce non-reduced	0.0336*** (6.50)	0.0601*** (7.76)	0.0392*** (4.12)
Av. cents per ounce reduced	-0.0283*** (-10.63)	-0.0210*** (-6.22)	-0.0187*** (-5.38)
N (obs)	17,993	8,848	5,806
N (groups)	377	149	147
Adj. R-sq (within)	0.5390	0.5414	0.5510
Adj. R-sq (between)	0.7750	0.6454	0.6441
Adj. R-sq (overall)	0.5793	0.5797	0.5553
t-statistics in parentheses			
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$			