Category Optimizer™: A Dynamic-Assortment, New-Product-Introduction, Mix-Optimization, and Demand-Planning System

Ashish Sinha
Anna Sahgal
Sharat K. Mathur

Date: March 18, 2012

Please do not cite without the First Author’s Permission

(Runner-up Gary Lilien Practice Award 2012)

Ashish Sinha is Professor and Head, School of Marketing, Australian School of Business, University of New South Wales, Sydney, Australia; Anna Sahgal is Principal, AS Marketing Associates, Sydney, Australia; Sharat K. Mathur is a Senior Vice President at the Symphony IRI Group, Chicago, USA. Please address all correspondence to the first author at the following address: Quad 3036, School of Marketing, Australian School of Business, UNSW, Kensington, Sydney, Australia 2052; e-mail: a.sinha@unsw.edu.au; phone: 61.2.9385.9699. We thank John Roberts and Peter Popkowski Leszczyc for providing extensive feedback on an earlier draft of the paper and Tanvi Mehta for copyediting the paper. The usual caveat applies: all omissions and errors are the responsibility of the authors.
Category Optimizer™: A Dynamic-Assortment, New-Product-Introduction, Mix-Optimization, and Demand-Planning System

Abstract:

The purpose of this paper is to describe the implementation of a category management tool, known as Category Optimizer, at Foster’s Wine Estate Americas for one of its brands—Beringer California Collection (BCC). Fosters was facing a common management problem: that of harnessing its portfolio of Beringer California Collection wines to increase profitability, improve its competitive position, and defend against a disruptive new entrant in the U.S. wine market called [yellow tail]. Category Optimizer™ combines the parsimony of an internal market structure with the advances that have been made in assortment planning in operations research, assortment and Stock-Keeping-Unit (SKU) level modeling, mixed logits, and the marketing literature on the perceptions of variety of assortment to develop and estimate a model on readily available store scanner data. The model subsequently uses these results to inform strategic and tactical decision-making. This approach led to recommendations that initially seemed counter-intuitive; the normal response would be for Fosters to consider lowering price to maintain share and volume, a strategy not inconsistent with many of the recommendations of Hauser and Shugan’s (1983) Defender model. However, considering the additional degrees of freedom that a product range offered for defense, we demonstrated that a combination of price increase together with the introduction of a volume-flanker product in a new channel would improve profits, increase revenue, and protect and enhance market share. These were successfully implemented in early 2008, earning rich dividends for the company, increasing profitability by 70%, revenue by 3%, EBIT by 8.5%, while also having a positive impact on its brand ranking: in 2008 it debuted at number six among the international wine brands. It also managed to play an important role in deposing the market share leader, [yellowtail], from its dominant position. We conclude the paper by providing examples of other companies where this approach has also been successfully implemented, and by discussing some avenues for future research.

Keywords: Disruptive Innovations, Category Management, Internal Market Structure, Assortment, Perception of Variety, Brand Portfolio
Category Optimizer™: A Dynamic-Assortment, New-Product-Introduction, Mix-Optimization, and Demand-Planning System

The purpose of this paper is to describe the implementation of a category management tool, called Category Optimizer™, at Foster’s Wine Estates Americas for one of its brands, Beringer California Collection (BCC). Category Optimizer™ is an advanced analytical tool used by retailers and manufacturers alike to make decisions about assortment, price optimization, and demand planning. It uses readily available store-level scanner data to estimate a market share model, and subsequently uses these results to inform strategic and tactical decision-making. It combines and advances literature in disparate areas of assortment planning in operations research (Kök & Fisher, 2007), internal market structure (Elrod & Keane, 1995; Popkowski Leszczyc, Sinha, & Sahgal, 2004), assortment and Stock-Keeping-Unit (SKU) level modeling (Inman, Park, & Sinha, 2008; Sinha, Inman, Yantao, & Park, 2005), aggregate logit modeling (Chintagunta, 2001, 2002), mixed logits (Sinha, 2000), and the marketing literature on the perceptions of assortment (Hoch, Bradlow, & Wansink, 1999). The case illustrates the use of this tool by BCC to respond to a highly challenging situation of falling market share and profitability and increased competitive pressure, increased by the threat from a disruptive innovation in the form of [yellow tail] that took the United States and the world by storm, and which in turn changed the competitive landscape of the wine industry. Using a market-driven strategy of sensing, dissemination, and response, BCC not only managed to increase profitability, market share, and brand equity but it also minimized the effect of [yellow tail]’s presence on its own franchise while playing an important role in deposing [yellow tail] from its dominant position.

While Category Optimizer borrows its methodology from aggregate-level market share models, much of the research has been applied to extremely small data sets that have a few SKUs, rendering these models inapplicable to most practical settings. In that respect, an important contribution of this
work is to develop a system that is applicable to large-scale problems commonly found in applied settings. We make four important contributions. First, we propose an assortment-planning tool that is grounded in consumer behavior theories such as perception of variety, attribute-information processing, and similarity and dissimilarity of SKUs. Second, we develop an analytical solution that provides managers with the ability to understand the role of assortment planning systems on channel acceptance of a new product. Third, we develop an assortment-planning tool that is applicable to ‘real life’ large-scale optimization problems. Lastly, our solution optimizes both the assortment of products and the marketing mix for each of the products in the category. To the best of our knowledge, this is the first attempt to provide such a solution in either academia or the practice of marketing.

We report our research in the following manner. We first outline management problems being faced by Fosters. This is followed by a description of the general approach and the methodology used in this project. The next section describes how the approach was applied in order to generate a strategy for Fosters. We then describe the outcome of the implemented strategy, and provide evidence of the impact that our recommendations have had on the performance of the business. This is followed by a brief description of the various projects that Category Optimizer™ has been used for. We conclude the paper with a discussion about the future opportunities that this stream of research provides.

The Case of Beringer California Collection

Operating as three regional businesses in Australia, Asia, and the Pacific; in the Americas and Europe; and in Middle East and Africa, Foster’s Group owns, markets, and distributes an international portfolio of beer, wine, spirits, cider, and non-alcoholic brands. Internationally, it produces, markets, and exports the world’s leading portfolio of premium wine brands including Penfolds, Wolf Blass, Rosemount, Lindeman’s, Saltram, Seppelt, Wynns, and Yellowglen from Australia; Beringer, Etude,
Stag’s Leap, and Chateau Souverain from North America; Matua Valley and Secret Stone from New Zealand; and Castella de Gabiano from Italy.

**Problem Statement:** Foster’s acquired Beringer winery in 2000 for AUD 2.6 billion. Beringer Wine Estates was a market leader in California’s premium wine industry. The company consisted of six award-winning Californian wineries: Beringer Vineyards, Meridian Vineyards, Chateau St. Jean, Chateau Souverain, Stag’s Leap Winery, and St. Clement Vineyards, plus an imported portfolio of premium brands from Italy, France, and Chile. Beringer had an excellent range of strongly branded successful products, including Chateau St. Jean 1996 Cinq Cepages cabernet sauvignon, which was awarded Wine of Year in the 1999 Wine Spectator ‘Top 100’. Beringer also controlled more than 10,000 acres of vineyard land, all in the coastal region of California.

Acquiring Beringer gave Foster’s a firm foothold in the American market, and initially provided rich rewards in terms of higher revenue and profitability. However, by 2004 Foster’s wine division reported a profit of merely USD182 million, which was down by more than 21% from the previous year’s profit. The confluence of several factors played an important role in creating a difficult situation for Foster’s: an oversupply of wine, particularly in California; tight competition; the increasing value of the Australian dollar; and the increased cost of procuring grapes. In addition, the increase in the cost of electricity and other power sources in California in the subsequent years made it very difficult for Foster’s Americas to remain profitable. Some analysts felt that Fosters had over-paid for the acquisition. Of all the different product lines, Beringer California Collection (BCC) was the hardest hit as it was positioned in the highly competitive, lowest price tier of USD 4–6. Given that the cost of producing wine had escalated dramatically, BCC was seeing an erosion of profits and revenue.

*Increased Competitive Pressure and the Rise, Rise, and Rise of [yellow tail]:* On top of the cost pressures that BCC faced, the intensity of competition (particularly in the grocery channel, BCC’s
primary distribution channel) had increased substantially. Since 2002, the top 10 brands of wine, of which nine were in the lower price tier, had been losing market share, and by 2007 the cumulative market share for these brands had dropped by over 33%. By 2007, the market was so configured that 60% of the active brands in the grocery channel were ones that had been introduced only after 1999, and these new brands accounted for 18% of the market share. By 2006, BCC was no longer in the top 10 wine brands. In addition, it needed to be wary of cheap wine imports from all over the world. One such new brand that bucked the downward trend was [yellow tail]. Introduced in 2000, it began dominating the wine market the world over within a few years, including in the United States, and particularly in the grocery channel. Kim and Mauborgne (2005) argue that [yellow tail] succeeded by “creating uncontested market space and making the competition irrelevant”—a Blue Ocean Strategy that changed the competitive landscape. [yellow tail] managed to target beer drinkers rather than wine drinkers by largely distributing its product through the grocery channel, the preferred channel of beer drinkers for the purchase of liquor. Taken together, [yellow tail] disrupted the wine market by using a market driving strategy—not by doing things better but by doing things differently, the hallmark of all disruptive innovations (Christensen 2000). Interestingly, it raised the price of its wine above the budget market, line pricing its products at $6.99. By 2006, [yellow tail] had become a firm disruptor (Sood and Tellis 2011), gaining the top spot in the United States and garnering 3.15% of the market share in the grocery channel.

**BCC’s Dilemma:** While a success story was unfolding in the form of [yellow tail], BCC found itself in a position of vulnerability. Its zinfandel varietal was a starter wine aimed at the uninitiated wine drinker, the same target market as that of [yellow tail]’s. BCC’s “blush” line was predominantly pink, comprising the white and red zinfandels, white merlot, and rosé. What could BCC’s management learn from [yellow tail]’s experience? Given the positive response that chardonnay, cabernet sauvignon, and
merlot received in the grocery channel, wouldn’t it make sense for it to introduce these varietals? Chardonnay was and is one of the most successful varietals in the United States, with 22% market share growing at a rate of 4% in 2007. But to do so, BCC first needed to understand the competitive interaction between its current products and the proposed introductions.

While these introductions would help defend its turf, this would not solve the problem of razor-thin margins that was leading BCC to lose money. The price of the product line would have to be increased. [yellow tail]’s experience showed that the market could support such a price increase. However, it was not certain if this would carry over to BCC’s franchise. What about BCC’s brand equity—was it similar to that of [yellow tail]’s? This analysis led BCC to consider a contra-strategy of increasing the price by up to a dollar. However, it was unclear what the impact of a 20% price increase would be on market share, revenue, and profits. To make up for the lost market share that would result by taking a price increase, BCC decided to introduce a few new varietals in sequence, such as chardonnay, merlot, and cabernet in conjunction with the price increase. It is fair to say that both internally and externally the proposal to increase price by 20% was resisted.

What would be the loss of market share if the price were increased by 5%, 10%, 15%, or 20%? What percentage price increase would lead to an increase in revenue? Would the price increase push loyal customers to the next quality tier of Beringer’s wine? Would the new introductions lead BCC’s zinfandel varietal to lose share to the overall detriment of the franchise? Which varietal should BCC introduce first? What would the impact of these introductions be on the franchise? Would it grow the franchise or cannibalize the existing products, leading to a redistribution of volume, but with no overall growth? These were questions that required empirically based answers before an important decision of this nature could be made for their largest product line.
**The Solution:** Foster’s Wine Estate Americas’ managing director commissioned a boutique Chicago firm to help them provide answers to some of these questions. This boutique firm used the services of AS Marketing International (ASMI) to come up with an analytics based solution. As Foster’s owns a portfolio of brands in the wine category, it was not only interested in understanding the impact of price increase on Beringer, but also on the other brands that it owns. In addition, Foster’s also required recommendation for a varietal introduction. Therefore, it was decided that an SKU rather than a brand-level model be estimated. Category Optimizer™ was applied to the USD 4-6 price tier which comprised of approximately 3,000 SKUs. In the section below, we describe the approach and methodology used by Category Optimizer™ followed by the section on findings for the Foster’s study.

**Approach and Methodology**

We build on Kök and Fisher’s model (2007) in which the total demand for a product is assumed to be due to transferable (substitutable) and non-transferable (non-substitutable) demand. Transferable demand can be defined as the portion of the total volume of a product that other products in the assortment would gain, if it was deleted, while non-transferable volume is the portion of the total volume that would be lost if a particular product is deleted. The demand model is informed by a neo-Lancastrian approach (Louviere, Hensher and Swait 2000) rather than a Lancastrian approach, the important distinction being that consumers in the former paradigm are assumed to buy products for the benefits that the features of the product provide (e.g. brand, size, etc.) rather than the feature itself. Previous work in the areas of assortment and aggregate mixed logit models (Berry, Levinsohn and Pakes 1995) uses features (e.g. brand, size, etc.) and feature levels (e.g. Coke and Pepsi) to identify different characteristics of a product and assortment, for instance variety and reduction in assortment size (Boatwright and Nunes 2001). However, these studies assume that the extent to which a feature level is different from all the other feature levels is the same. An attribute-based methodology (Sinha, Inman,
Yantao, & Park, 2005) on the other hand assumes that competition among brands is, for instance, due to underlying attributes or benefits (i.e. quality and taste), and that two brands in a consumer’s decision set may be perceived as similar (i.e. Coke and Pepsi) yet distinct from another brand (i.e. Mountain Dew). This is a distinct advantage of the proposed approach. The model used to estimate the transferable and non-transferable demand function is provided in the technical appendix.

**Results and Discussions**

The data set comprised of approximately 3,000 SKUs across 54 accounts for two years, from January 2005 to December 2006. These SKUs were described by four different features: brand, size, varietal, and country of origin, with brand having twenty five, size having three, varietal having fourteen, and country of origin having seven levels. Price and promotional and distribution information were also included in the analysis. As BCC’s intent was to introduce new varietals to its predominantly “blush” wine offering, the management needed an understanding of the degree of competitive interaction between different feature levels—for instance, varietals. Specifically, BCC’s management was interested in understanding the competitive interactions between its blush offerings (dominated by white zinfandel) and chardonnay, cabernet, and merlot. Figure 1 provides a graphical representation of the process for model estimation.¹

---

**Insert Figure 1 about here**

---

We now turn our attention to providing details for the analysis of varietals. Figure 2 provides a map of the varietals, showing some degree of competitive interaction between “blush” wines and other varietals. The map also shows that chardonnay does not compete that closely with the “blush” varietals of zinfandels, white zinfandels, and white merlot, implying that chardonnay would be a great addition to

---

¹ Table A.1 in the appendix provides the parameter estimates for different features and feature levels.
BCC’s current product line. A similar analysis of the “attractiveness” or equity of the different varietals, provided in Figure 3, which are obtained by exponentiation of the coefficients for the different varietals of the logit model (mean coefficients provided in Table A.1 for varietals), shows that both chardonnay and white zinfandel are the most preferred varietals, with zinfandel being the least preferred of all. Of the red varietals, pinot noir has the highest attraction score. Combining the results from the different analyses, we recommended the introduction of a pinot noir, a merlot, and a cabernet sauvignon to the market, with a simultaneous introduction of chardonnay at an increased price. This particular recommendation was provided based on the analysis showing a lack of competition between chardonnay and BCC’s “blush” varietals, implying that introducing a chardonnay would be largely incremental to BCC’s franchise. The introduction of the chardonnay should be followed by the introduction of the pinot noir, the merlot, and the cabernet sauvignon, though we were indifferent between the introduction of merlot and cabernet sauvignon.

A similar analysis of brands showed that BCC and [yellow tail] had the highest brand equity, implying that as the market had already borne a price premium of a dollar above the budget range for [yellow tail], a similar increase of price for BCC, given its brand equity, could be supported by the market. A second stage of the analysis consisted of simulating the effect of price increase and the simultaneous release of new varietals. We used the technique provided by Inman, Park and Sinha (2008) to optimize the effect of the price increase and introduction of the new varietals on the market share and volume under strategic and managerial constraints. The average price elasticity of the “blush” category was approximately .86, which implied that an approximate 20% increase in price would lead to a decrease in share of 17%. Given the cost structure of the business, this price increase was required for the profits to
return to positive. However, a simultaneous release of the chardonnay would make up for lost market share. We also identified pinot noir as a varietal that has a huge potential in this price tier; however, given the expensive grapes that are required for its production, the company decided to explore this opportunity later.

**Impact of the Project:** The project was delivered in June 2007. It had the full support and involvement of the managing director of Foster’s. The senior management was closely involved in the project and the authors helped them make numerous decisions. The study provided important inputs to the senior management’s decisions. For instance, the management expected a push back from both the company’s sales force and retailers. The price simulator was used as a way of showing the sales force and the retailers various “what if?” scenarios to understand the ramifications of potential competitor reactions. McKinsey Corporation was hired to help with the implementation of this strategy in July 2007. We note that a triple mix strategy, which includes a price increase coupled with new product introductions in a new channel, is not common in the fast moving consumer goods (FMCG) industry. The successful implementation of this strategy required stakeholders, shareholders, retailers, employees and senior management to completely buy into these actions, and it took the organization, with the help of external consultants, over 6 months to do so.

Figure 4 provides the timeline for BCC’s implemented strategy. The price increase, with the simultaneous introduction of chardonnay, was implemented in early 2008 followed by the introduction of cabernet sauvignon and merlot in the second half of the year. As predicted, BCC lost 14% of its market share; however, its revenue increased by .7%. By the end of 2008, BCC’s chardonnay line was
ranked the number one new wine of the year in the U.S. based on both volume and dollar sales,\textsuperscript{2} while the cabernet sauvignon and merlot were ranked the two most top selling varietals of the second half of 2008.\textsuperscript{3} These introductions made up for the loss of market share due to the price increase. By the end of 2008, BCC increased its profitability by 70\%, its revenue by 3\%, and arrested its slide in market share, which was down by only 10\% in comparison to 17\% at the beginning of the year. By the end of 2009, BCC had regained its lost market share. As for [yellow tail], it lost its dominant position in 2009 due to numerous strategic and tactical innovations introduced by its incumbents, including BCC. These outcomes show that our empirical results are consistent with those of Sood and Tellis (2011). They find, too, that the disruptor in many instances dominates the industry only for a few years, losing its position as incumbents respond to the disruptor.

\textit{Organization-wide Impact:} Not only did this project have tangible financial benefits, it also had a significant impact on the organization by substantially increasing its brand equity and also putting it on a path of innovation by introducing new varietals (such as Muscato) in new channels (Drug and Mass-Merchandiser channels). Intangible Business, a UK-based firm, identifies the top 100 international wine and spirit brands in its annual survey every year since 2006, using a mix of hard and soft measures such as whether the brand is forward looking, measured by projected brand growth and market shares. In 2006 and 2007, Beringer did not make the list, while in 2008, as a result of the implemented strategy, it debuted at number 44 among the wine and spirits brands, and at number six among the international wine brands. In addition, Beringer among the American wine and spirits brand was ranked number 8 in 2008, while did not make the cut in either 2006 or 2007. This demonstrates that the project not only had tangible financial benefits, but significant long-term positive benefits that had organization-wide cultural ramifications that put it on a path of innovation.

\textsuperscript{2} According to Nielsen new wine item reports for 52 week period ending December 13, 2008. \\
\textsuperscript{3} According to Nielsen new wine item reports for 26 week period ending December 13, 2008.
The project had a big impact across the organization. When the CEO of Fosters, Trevor O’Hoy, unexpectedly resigned in June 2008, the company issued a write-down of AUD700 million of its global wine business, linked primarily to the purchase of Beringer and Southcorp a few years before. Given the losses of Foster’s American wine business, the level of scrutiny from investors was intense. In his annual investor’s speech on the state of the business in 2009, Angus Mckay, the Chief Financial Officer of Foster’s, said the following (CEO and CFO addresses 2009):

One year on from the price increase it is worth highlighting the development of the broader Beringer California Collection and the increased levels of profit flowing from this brand […] The expanded California Collection provides retailers with a strong Beringer branded varietal set in the fast growing $4-6 price point. This is a significantly enhanced position compared to the primarily pink wine offering we had a little over 12 months ago. And while Beringer White Zinfandel volume is as expected below the prior year, unit profitability and earnings are up […] Over the next 6 months as we start to lap the price increase we expect an improvement in the comparative performance of Beringer White Zinfandel. We also expect the broader California Collection to continue to benefit from the expanded varietal offering and increased distribution.

This speech demonstrates both the importance of the project and the organization-wide impact it had at Foster’s.

*Generalizability of Category Optimizer™:* As mentioned in the introductory section, we have successfully implemented this analytics product in many other companies. ASMI partners with numerous consulting houses to implement these projects for a wide array of clients, and its current and ex-partners include Synovate MMA in the US, Synovate Aztec and Summit Insights in Australia, and Genpact in India. Several companies that have used this analytic product are P&G, Merisuant, and GSK in Australia, and Johnson & Johnson and Home Depot in the U.S. for obtaining insights for both durable and non-durable product categories in varied areas of new product introduction, price optimization, and assortment optimization and also for broader strategy issues that cut across several areas mentioned above. This demonstrates the generalizability of the solution and its applicability to diverse geographical
settings and managerial problems. This solution has impacted over USD 9 billion dollars of sales. Dan Eggleston of Synovate MMA, in his testimonial, says the following:

MMA has leveraged the Category Optimizer since 2008, providing our clients with critical insights and actionable recommendations to manage their product portfolio within their respective categories. Our clients have been able to realize true value through the Category Optimizer’s simulation capabilities and have been very pleased with the recommendations that have resulted. We will certainly continue to use this methodology to provide these types of insight to our clients on a go-forward basis.

**Conclusion**

The purpose of this research was to demonstrate the effectiveness of Category Optimizer™, a category-management tool that extends and builds on the current literature in the area of assortment planning by combining recent advances in the area of internal market structure, perception of variety, and operations research, particularly in the area pertaining to assortment. We describe the application of this product to the case of Beringer Californian Collection, a wine label that found itself in a difficult position due to industry, competitive, and market forces. The wine market was disrupted by an Australian brand, [yellow tail], that went from being unknown to being one of the most successful brands in the history of the wine industry. The case shows that being a “fast follower,” which entails learning from the disruptor, adapting, and responding quickly are ways by which the advantage gained by a disruptor can be negated or minimized. We also briefly discuss how the analytic product, Category Optimizer™ has been used the world over by a number of FMCG, pharmaceutical and retail companies to provide insights into a plethora of problems related to category management.
References

*Econometrica*, 60 (4), 841-890.


Figure 1
Modelling for BCC Project

• SKU Level Model
• 3000 SKUs were defined by 4 Features:
  Brand (25); Sizes (3); Varietals (14); Countries (7)
  Controlled for Price, Distribution and Promotional Variables

Transferable Demand Function
Non-Transferable Demand Function
Optimize and Simulation

Perceptual Maps for 4 Features (Each Map has 2 Dimensions)
Estimate Attractiveness of each Feature Level
Calculate Own and Cross-Price Elasticities

Step 1 → Calculate Uniqueness of each SKU
  (Using Maps for 4 Features)
Step 2 → Calculate Incrementality using Category Model

Run Simulations at Different Price points and for Different Innovations

Figure 2
Competitive Map for Wine Varietals
Figure 3
Varietal Attractiveness or Equity Scores

![Bar chart showing varietal attractiveness or equity scores for different wines.]

Figure 4
Timeline for the Implemented Strategy

![Timeline diagram showing the timeline for the implemented strategy.]

- Price Increase in January 2008
- Chardonnay introduced January 2008
- Cabernet Sauvignon introduced June 2008
- Pinot Noir introduced 2009
- Price increases in other markets late 2008
Technical Appendix

Transferable Demand Function: The demand model is estimated at the SKU level—under the assumption that the demand for an SKU is the sum of the preferences that consumers have for the set of attributes that the SKU possesses—and is controlled for the effects of the marketing mix variables, such as price advertising, promotion, and couponing (Inman et al., 2008). We estimate the demand model using an aggregate level mixed logit model (Chintagunta, 2001; Sinha, 2000). The advantage of this methodology is two-fold: Firstly, demand drivers at different levels of geography, (e.g. a store, a cluster of stores, a region, chain or at a national level) can be estimated, and based on that information appropriate adjustments to the assortment can be made. A second advantage of this methodology is that consumer heterogeneity for features and feature levels can be represented in reduced space, usually two dimensions for each feature. This allows us to map different SKUs in an N x 2 perceptual space, where N is the number of features and 2 is the number of dimensions/attributes for each feature.

The underlying assumption of this framework is that consumers do not buy features, such as brand, size or flavor, but rather the benefits (also called attributes) that are accrued from these features, such as quality and taste for brands. The added advantage of having the market structure as a part of the analysis is that mixed multinomial logit (MNL) models do not suffer from IIA (Fair Share), which is a problem of the aggregate MNL model.

The model is set out as follows:

It is assumed that the utility derived by the $i$-th individual for the $j$-th SKU at the $t$-th time period is given by:

$$ U_{ijt} = V_{ijt} + e_{ijt} \quad (A.1) $$

where,
\( V_{ijt} \) is the deterministic component of the utility, and \( e_{ijt} \) is the random component of utility assumed to have a Gumble distribution.

In addition, it is assumed that the deterministic component of utility is given as follows:

\[
V_{ijt} = \gamma_{ij} + \sum_{m} \alpha_{im} \times x_{mjt}
\]  
(A.2)

where,

\( i \) indexes consumers, \( j \) indexes SKU, \( t \) indexes time period and \( m \) indexes marketing mix variables. \( \gamma_{ij} \) is the intercept term, \( \alpha_{im} \) are the set of parameters that measure the effect of \( m \)-th marketing mix variables, and \( e_{ijt} \) is the random component of utility.

We also assume that the intercept term \( \gamma_{ij} \) is a function of the feature-level that a product possesses, for example the brand, size, and flavor of the product in case of an FMCG product, though the solution is generalizable to the durable and non-durable product categories. Therefore, the intercept is represented as follows:

\[
\gamma_{ij} = \sum_{k} \sum_{n} \theta_{ikn} \times \delta_{knj}
\]  
(A.3)

where,

\( k \) indexes feature level, and \( n \) indexes features, and,

\[
\delta_{knj} = 1, \text{ if } j \text{-th SKU possesses the } k \text{-feature level of the } n \text{-th feature,}
\]

\[
= 0, \text{ otherwise.}
\]

We also assume that \( \theta_{in} \) has the following distribution:

\[
\theta_{in} \sim N(\overline{\theta}_n, \Sigma_n)
\]  
(A.4)

A principal component decomposition of the variance–covariance is assumed that allows us to capture the variability across individuals in reduced space.
\[ \Sigma_n = L_n L_n^T \]  \hspace{1cm} (A.5)

Similar to Elrod and Keane (1995), we note that the \( L \) matrix represents the perceptions that consumers have for \( K \) feature levels of the \( n \)-th feature. There are several advantages of this methodology. For one, the principal component structure allows the representation of the variance–covariance matrix in reduced space. In addition, unlike the logit model, the mixed logit model described above does not suffer from the IIA problem. Therefore, we contend, a model of this type is ideal for understanding and calibrating the impact that the deletion or addition of products has on existing products and brands. In addition, unlike the log–log pricing models, cross-elasticities are easy to obtain without having to estimate \( J \times J \) number of parameters for measuring cross-elasticities.

The probability of the \( i \)-th individual purchasing SKU \( j \) in the \( t \)-th time period is given by:

\[
P_{ijt} = \frac{\exp(V_{ijt})}{\sum_{j'} \exp(V_{ij't})}. \quad (A.6)
\]

Given that the data, in the form of market share, is observed at the aggregate level—i.e., the share for the \( j \)-th SKU in the \( t \)-th time period in the \( a \)-th account is only observable—rather than at the level of individual choices, it is necessary for us to use an aggregate level logit model (Chintagunta 2001; 2002). Given the set of coefficients, account level data, prices, and promotional activity it is easy to estimate the coefficients for the model, details for which can be found in Chintagunta (2002), among others.

**Non-Transferable Demand Function:** We now provide a description of the procedure used to estimate the non-transferable demand function. A direct method often used in aggregate level logit model analysis is the use of the outside good as a way of controlling for the non-transferable demand function. However, as noted by Kök, Fisher and Vaidyanathan (2006), the coefficient for the outside good sets both the rate of category penetration and the extent of non-transferable function, which is a highly unattractive feature of this solution. We also contend that unless the attractiveness of the outside good is made a function of the assortment characteristics, such as variety and size, which to the best of our
knowledge have never been implemented in models that exist in this area, the proportion of the non-transferable demand is a function of the attractiveness of the outside good for all SKUs in the category. We contend that this is by far the most unattractive feature of the existing “outside good” solution that is widely used in marketing (for example, Chintagunta 2002). In addition, we note that there are several ways of calculating the market share for the outside good, and Chintagunta (2002) claims that the results obtained for transferable demand function are invariant to the methodology used for this calculation. This result implies that on one hand the parameters for the transferable demand function are stable and invariant to the specification of the “outside good;” on the other hand, it also points to the problems with using this method to calibrate non-transferable demand function. Different coefficients for the preference of the outside good are possible, and the one chosen by the researcher may lead to biased and/or erroneous results.

One approach that has been proposed both in marketing and operations research (Kök and Fisher 2007) is the use of stock-out data to calculate the extent of non-transferable demand function. However, this solution requires both inventory and sales data at a store level to be available. For manufacturers, this data is impossible to obtain. In addition, solutions that have been proposed using this data (Kök and Fisher 2007) estimate the proportion of non-transferable demand volume to be constant for all SKUs in the category. In order to alleviate the problems associated with both solutions provided above, we use the approach described below.

**Category Level Model Approach:** We calculate the uniqueness scores for each SKU. As the location of the products is available as an N x 2 perceptual space, these locations in perceptual space are used to calculate Gower distance (Gower 1971) for each SKU. There are two major advantages of attribute-based Gower distance over the commonly used hamming distance (Hoch, Bradlow, & Wansink, 1999) and entropy measures (Herpen and Pieters 2002). Firstly, the attribute-based measures assume that all
differences are not the same; for instance, this procedure assumes that Pepsi and Coke are more similar to each other than they are to Mountain Dew. Secondly, Gower distance can be standardized such that each SKU is assigned a uniqueness score between 0 and 1, where 0 means that the SKU is not unique to the assortment, while 1 means that it is different from all products in the assortment.

The basic premise of our approach is that there are numerous natural experiments unfolding in the environment simultaneously, providing variability in the data to estimate the incrementality due to each SKU. In any given time period, an SKU is available only in a few stores. Therefore, stores in which products are available and sold will have an impact on category volume, and stores where the SKU does not sell or is not available will not have an impact on category volume. Secondly, even if a particular SKU is available in a store, the uniqueness of this SKU in that store is different from the uniqueness of the same SKU in another store. We use these uniqueness scores, together with whether an SKU sells in a particular store and the average price to develop a category level model in order to allow us to calculate the unique volume contributed by each SKU in the category. To the best of our knowledge, we have devised the first procedure in either academia or the practice of marketing that allows us to estimate the non-transferable volume at an SKU level without requiring stock-out information.

The category level sales can be specified as follows:

\[ Q_{at} = \mu_a \prod_j \left( S_{ajt}^{\rho_{aj}} \right) \left[ \bar{P}_{at}^c \right] \varepsilon_{at} \]  \hspace{1cm} (A.7)

where,

- \( a \) – indexes accounts,
- \( t \) – time period,
- \( j \) – indexes SKUs,
- \( Q \) – is the category volume,
- \( S \) – is the sales volume for different SKUs in the category,
- \( \bar{P} \) – is the average price level,
- \( c \) – is the category level price elasticity,
- \( \mu \) – is the intercept term, while \( \varepsilon \) is the error term,
- \( \rho_{aj} \) – is the proportion of the non-transferable demand function for the \( j \)-th SKU in the \( a \)-th account.
We note that $\rho_{aj}$ measures the unique contribution of the $j$-th SKU in the $a$-th account. One major limitation of the proposed approach is the large number of parameters, equal to the number of SKUs, that need to be estimated to calibrate the unique contribution each SKU makes to the overall category volume. In addition, given that one of the most important purposes of this system is to understand the impact of product innovation on redistribution of volume as well as the effect of the introduction on category volume, SKU-specific parameters will not allow the system to extrapolate the effects of new introductions on category volume. To remove the limitations discussed above, we re-parameterize $\rho_{aj}$ as follows:

$$\rho_{aj} = \rho^* (Uniq\text{ue}_{aj}) \quad (A.8)$$

where,

$Uniq\text{ue}_{aj}$ is the Gower distance based uniqueness score that varies between 0 and 1, and, $\rho^*$ is the normalizing coefficient, easily estimable from the available data. Different values of $\rho^*$ imply a different extent of non-substitutable demand function. For instance, a value of 1 implies a linear relationship between uniqueness scores and non-substitutable demand volume, while a value of 0 implies that the entire volume of an SKU is transferable to other SKUs in the category. Knowing $\rho^*$ and the unique scores for any new SKUs, we are able to predict their non-substitutable demand function. This is an important advantage of our methodology not shared by other assortment solutions. Another important advantage of this approach is the dynamic nature of the unique score. For instance, the uniqueness score of an SKU is dependent on the mix of the products in the assortment. This implies that the uniqueness of an SKU will change, and therefore so will its contribution to the overall category volume, based on the size and the mix of products in the assortment. This makes the assortment problem
dynamic as the non-transferable volume will change dependent on the mix and size of SKUs left in the assortment, once a certain set of SKUs are added or deleted.

Assortment and Price Optimization: Once the transferable and non-transferable demand function for every SKU at different levels of geography (store, chain, and national level) in the category has been calculated, we use a Genetic algorithm to optimize the assortment. In particular, this product has been used to help FMCGs sell-in innovations to different chains. The assortment optimization problem can be recast as a 0-1 Knapsack problem, in that the total number of SKUs in a category is fixed, and the set of products that maximize category volume, revenue or profitability is identified, based on the price, promotion, and attribute coefficients (Kök and Fisher 2007). While it has only recently been recognized in academia that channel acceptance is the first stage to the eventual success of a new product (Luo, Kannan, Ratchford, & Hall, 2007), this issue has existed for a long period of time in the practice of marketing. Our method allows companies to assess whether a new product idea will increase (or decrease) category volume or profitability. These numbers are of direct interest to a retailer, and therefore manufacturers can often fight delisting or reduce slotting fees dependent on the outcome of the simulations.
<table>
<thead>
<tr>
<th>Features</th>
<th>Mean</th>
<th>Dim 1</th>
<th>Dim 2</th>
<th>Features</th>
<th>Mean</th>
<th>Dim 1</th>
<th>Dim 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est (SE)</td>
<td>Est (SE)</td>
<td>Est (SE)</td>
<td></td>
<td>Est (SE)</td>
<td>Est (SE)</td>
<td>Est (SE)</td>
</tr>
<tr>
<td>Brand 1</td>
<td>-0.35(.01)</td>
<td>0.50(.06)</td>
<td>0.00*</td>
<td>1.5 L</td>
<td>0.43(.01)</td>
<td>0.21(.02)</td>
<td>0.00**</td>
</tr>
<tr>
<td>Brand 2</td>
<td>-0.18(.01)</td>
<td>0.04(.05)</td>
<td>0.19(.04)</td>
<td>187 MLS</td>
<td>-0.21(.02)</td>
<td>-0.17(.03)</td>
<td>0.21(.02)</td>
</tr>
<tr>
<td>Brand 3</td>
<td>-0.46(.01)</td>
<td>-0.10(.04)</td>
<td>-0.05(.04)</td>
<td>750 MLS</td>
<td>0.00</td>
<td>-0.01(.03)</td>
<td>-0.21(.02)</td>
</tr>
<tr>
<td>Brand 4</td>
<td>-0.12(.01)</td>
<td>-0.18(.04)</td>
<td>-0.04(.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand 5</td>
<td>-0.24(.01)</td>
<td>-0.04(.04)</td>
<td>-0.04(.04)</td>
<td>BLUSH_OTHER</td>
<td>0.15(.02)</td>
<td>0.54(.06)</td>
<td>0.00**</td>
</tr>
<tr>
<td>Brand 6</td>
<td>-0.39(.01)</td>
<td>0.06(.04)</td>
<td>-0.07(.04)</td>
<td>CABERNET</td>
<td>0.15(.01)</td>
<td>-0.07(.03)</td>
<td>0.00(.01)</td>
</tr>
<tr>
<td>Brand 7</td>
<td>-0.46(.01)</td>
<td>-0.08(.04)</td>
<td>-0.09(.04)</td>
<td>SAUVIGNON</td>
<td>0.30(.01)</td>
<td>-0.12(.03)</td>
<td>-0.04(.03)</td>
</tr>
<tr>
<td>Brand 8</td>
<td>-0.49(.01)</td>
<td>0.07(.05)</td>
<td>0.13(.04)</td>
<td>CHENIN BLANC</td>
<td>0.02(.01)</td>
<td>-0.10(.06)</td>
<td>-0.36(.05)</td>
</tr>
<tr>
<td>Brand 9</td>
<td>-0.36(.01)</td>
<td>0.07(.04)</td>
<td>0.05(.04)</td>
<td>SAUVIGNON</td>
<td>0.10(.01)</td>
<td>-0.08(.03)</td>
<td>-0.09(.03)</td>
</tr>
<tr>
<td>Brand 10</td>
<td>-0.33(.01)</td>
<td>0.17(.06)</td>
<td>0.29(.05)</td>
<td>MERLOT</td>
<td>0.14(.01)</td>
<td>-0.06(.03)</td>
<td>-0.01(.03)</td>
</tr>
<tr>
<td>Brand 11</td>
<td>-0.38(.01)</td>
<td>0.18(.06)</td>
<td>-0.29(.06)</td>
<td>PINOT GRIGIO</td>
<td>0.25(.01)</td>
<td>-0.10(.04)</td>
<td>0.15(.03)</td>
</tr>
<tr>
<td>Brand 12</td>
<td>-0.33(.01)</td>
<td>-0.16(.04)</td>
<td>0.06(.04)</td>
<td>PINOT NOIR</td>
<td>0.26(.01)</td>
<td>-0.09(.03)</td>
<td>0.09(.03)</td>
</tr>
<tr>
<td>Brand 13</td>
<td>-0.41(.01)</td>
<td>-0.15(.05)</td>
<td>-0.10(.04)</td>
<td>RED_NOIR</td>
<td>0.15(.01)</td>
<td>-0.08(.03)</td>
<td>0.21(.04)</td>
</tr>
<tr>
<td>Brand 14</td>
<td>-0.48(.01)</td>
<td>0.01(.05)</td>
<td>-0.02(.04)</td>
<td>RIESLING</td>
<td>0.23(.01)</td>
<td>0.06(.07)</td>
<td>0.49(.05)</td>
</tr>
<tr>
<td>Brand 15</td>
<td>-0.32(.01)</td>
<td>-0.03(.04)</td>
<td>0.01(.04)</td>
<td>WHITE MERLOT</td>
<td>0.07(.01)</td>
<td>0.03(.03)</td>
<td>-0.01(.03)</td>
</tr>
<tr>
<td>Brand 16</td>
<td>-0.32(.01)</td>
<td>0.08(.04)</td>
<td>0.10(.04)</td>
<td>WHITE ZINFANDEL</td>
<td>0.27(.01)</td>
<td>-0.05(.03)</td>
<td>-0.10(.03)</td>
</tr>
<tr>
<td>Brand 17</td>
<td>-0.31(.01)</td>
<td>-0.12(.05)</td>
<td>-0.20(.05)</td>
<td>WHITE OTHER</td>
<td>0.21(.01)</td>
<td>0.07(.03)</td>
<td>0.14(.03)</td>
</tr>
<tr>
<td>Brand 18</td>
<td>-0.40(.01)</td>
<td>0.25(.05)</td>
<td>0.02(.05)</td>
<td>ZINFANDEL</td>
<td>0.00</td>
<td>0.03(.03)</td>
<td>-0.04(.03)</td>
</tr>
<tr>
<td>Brand 19</td>
<td>-0.34(.01)</td>
<td>-0.02(.08)</td>
<td>0.47(.06)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand 20</td>
<td>-0.15(.01)</td>
<td>-0.13(.05)</td>
<td>-0.22(.05)</td>
<td>AUSTRALIA</td>
<td>-0.09(.01)</td>
<td>0.24(.05)</td>
<td>0.00**</td>
</tr>
<tr>
<td>Brand 21</td>
<td>-0.35(.01)</td>
<td>-0.06(.04)</td>
<td>-0.04(.04)</td>
<td>CHILE</td>
<td>-0.16(.02)</td>
<td>-0.29(.05)</td>
<td>0.00(.01)</td>
</tr>
<tr>
<td>Brand 22</td>
<td>-0.40(.01)</td>
<td>0.11(.04)</td>
<td>0.05(.04)</td>
<td>FRANCE</td>
<td>-0.04(.02)</td>
<td>-0.14(.07)</td>
<td>0.26(.06)</td>
</tr>
<tr>
<td>Brand 23</td>
<td>-0.50(.01)</td>
<td>-0.13(.04)</td>
<td>-0.06(.04)</td>
<td>GERMANY</td>
<td>0.00(.02)</td>
<td>0.11(.09)</td>
<td>0.37(.06)</td>
</tr>
<tr>
<td>Brand 24</td>
<td>-0.29(.01)</td>
<td>0.04(.04)</td>
<td>-0.02(.04)</td>
<td>ITALY</td>
<td>-0.03(.01)</td>
<td>0.20(.05)</td>
<td>0.02(.05)</td>
</tr>
<tr>
<td>Brand 25</td>
<td>0.00</td>
<td>0.10(.04)</td>
<td>0.00(.04)</td>
<td>OTHER</td>
<td>-0.02(.02)</td>
<td>-0.44(.08)</td>
<td>-0.28(.08)</td>
</tr>
</tbody>
</table>

|                  |         |         |         | USA          | 0.00    | 0.27(.06) | -0.21(.06) |

4 All maps suffer from reflection and rotational indeterminacies: for identification of the maps, one of the feature levels is constrained to lie along the positive half of dimension 1 (Brand 1 for Brands, 1.5 litres for size, Blush_other for varietals, and Australia for countries).