Portfolios: Patterns in brand penetration, market share, and hero product variants

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ABSTRACT

This research investigates the contribution of each stock-keeping unit (SKU) within a brand portfolio towards total brand penetration and market share, by adapting a method called Saturation Curve Analysis. The study utilises UK and US data on 90,000+ SKUs across 15 packaged goods categories. The results show that while the optimal number of SKUs in a portfolio is category specific, the top-selling SKU contributes around 50% of the brand penetration and 40% of sales. This establishes a benchmark for monitoring brand performance. These results emphasise the importance of having top-selling SKUs readily available to consumers, rather than sacrificing them over new product launches.

1. Introduction

As part of managing product portfolios, there is considerable focus on brands introducing new variants (Slater et al., 2014; Sok and O’Cass, 2015). Key reasons for new introductions include: appealing to new consumer segments (Kapferer, 2012); accommodating wider variety-seeking behaviours (Mason and Milne, 1994); guarding valuable shelf-space and/or responding to demands from retailers (Sorensen, 2009; Hubner and Kuhn, 2012; Chimbundu et al., 2015). However, introducing new products to market is risky with high failure rates (Castellion and Markham, 2013; Martos-Partal, 2012). Furthermore, brand owners need to invest significant resources to develop and support these new products, to maximise the odds of their survival in-market (Christensen, 2013; Slater et al., 2014). Typically, this will be at the expense of support given to the existing portfolio, as the company attempts to ensure that new product succeeds.

In order to measure the success of new introductions (as well as their older siblings in the portfolio), the question then turns to whether each product is effective in attracting incremental buyers to the brand. The extent to which each product attracts incremental brand buyers can be referred to as unique penetration. This is crucial, as brands grow principally through attracting more buyers (many of whom are light buyers) (Sharp, 2010; Romaniuk et al., 2014; Ehrenberg, 1972). Research shows that new introductions often disproportionately cannibalise current brand buyers rather than expand the pool of brand buyers (Lomax et al., 1997; Mason and Milne, 1994). Therefore, monitoring the health of the portfolio in terms of the role of what different products can offer to the overall performance is crucial.

Brand owners usually have ample data to monitor the in-market performance of their products (i.e. each variant and stock-keeping unit (SKU)). Syndicated data sources such as IRI, Nielsen, and GfK provide regular reports on unit sales, revenue, brand market share, and other brand performance measures. However, given the importance of penetration to brand growth, measuring both the unique buyers and incremental sales contributed by each product is crucial. In this research, in order to evaluate the contribution of each SKU to its’ portfolio, we develop a method called Saturation Curve Analysis, based on an existing saturation curve approach, that is grounded in natural and social sciences (e.g. Reed, 1925; Fisher and Raman, 2010; Srivistava, 1999). This method allows us to measure incremental buyers and sales from each variant towards the whole brand. We show an application of the method on data from the UK and the US and arrive at some crucial benchmarks on what to expect from the top selling SKU as well as the rest of the portfolio across many different conditions.

The research offers contributions for both academic and practitioner communities. For academia, the results form generalisable benchmarks in the area of portfolio management. Benchmarks allow comparisons as to whether products perform as expected, and enable predictions for future outcomes in similar circumstances (Barwise, 1995; Kennedy et al., 2014). For practitioners, knowing the expected contribution for each product in the portfolio is important for decision-making. Whilst companies actively monitor the sales performance of their products, knowing the unique buyer contribution of each product is often overlooked.

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Without evidence-based benchmarks, brand owners may underestimate the importance of the core SKUs in the portfolio and direct more resources towards newer products.

Importantly, the paper develops a method of evaluation that is readily understandable and does not rely on proprietary algorithms. This method informs brand owners to the extent of how much the top-\(n\) products in the portfolio contribute to overall brand buyers and sales. For the study, we analyse 13,681 brands and 92,877 SKUs across 15 packaged goods categories in the UK and US over multiple years, 2004–2006 in the US for Shampoo and Frozen Pizza, 2010–2012 in the UK for Dry Dog Food and Dry Cat Food, and 2012–2014 for Beer, Deodorants, Detergents, Frozen Baked Goods, Gum, Ice, Jams and Spreads, Shampoo, Shoe Care, Soap, Vitamins, and Yogurt. The US data is obtained from the IRI dataset (Bronnenberg et al., 2008) and the Nielsen datasets at the Kilts Center for Marketing (KiltsCenter, 2017), the UK data is sourced from Kantar Worldpanel.

The next section outlines the theoretical background to the study, followed by the data description and the methods employed for the analysis. The last section presents the results of the analysis.

2. Theory

In order to grow a business, apart from investing in distribution and advertising, brands have to ensure that their products are relevant to the market demands and satisfy consumers’ needs from the product category. Measuring revenue and unit sales from each product is part of these monitoring activities – to ensure each product attracts buyers. Brand owners may also enlist the aid of commercial assortment planning tools to help them monitor and plan their product offerings, such as the major assortment planning tools listed in Table 1.

These tools are typically based on proprietary algorithms and methods, that cannot be scrutinised objectively. They are predominantly intended to assist manufacturers for logistic purposes in managing inventory, distribution, shelf-space planning – and planning new additions to the portfolio by predicting the impact of assortment mix changes on consumer spending, revenue increases, and potential buyers (Hubner and Kuhn, 2012).

Excluding proprietary methods and algorithms, accumulated knowledge in consumer behaviour provides methods which can help evaluate product portfolios, such as applying the Duplication of Purchase analysis on the product portfolio. The Duplication of Purchase Law states that brands (or product variants and SKUs) share buyers according to their size in the market, i.e. greater sharing with more popular items than with less popular items (Ehrenberg et al., 2004; Lomax et al., 1997; Ehrenberg and Goodhardt, 1970). In the context of product portfolio management, the Duplication of Purchase Law provides a benchmark of the likelihood of two SKUs being purchased, based on the size of the SKUs in the portfolio (in terms of sales/revenue). The expected level of sharing between two SKUs can be computed using the following formula:

\[
\text{b}_{\text{AB}} = \frac{D\times \text{A}}{\text{A}}
\]

where \(\text{b}_{\text{AB}}\) is the percentage of buyers of SKU B who also buy SKU A in the chosen period, proportional to A’s penetration, and \(D\) (the Duplication Coefficient) is the average of the observed duplications for all pairs of SKUs, divided by the average penetration across all SKUs.

As a benchmark it allows brand managers to see if there is excess sharing and cannibalisation of SKU sales at the expense of another SKU in the portfolio (Lomax and McWilliam, 2001). One limitation of this approach is that, whilst we can ascertain the level of buyer duplication (“cannibalisation”) across all SKUs / products in the portfolio, i.e. \(A \cap B, A \cap C,\) and \(B \cap C,\) if SKU \(A, B,\) and \(C \in \text{Brand X,}\) we cannot determine the unique buyer contribution from each product from the Duplication of Purchase matrix, e.g. obtaining \(A \cap B' \cap C\) for the unique penetration contribution from SKU A. The focus on unique penetration contribution is crucial in portfolio health evaluation, as increasing penetration is identified as vital for brand growth (Sharp, 2010; Romaník et al., 2014; Ehrenberg, 1972).

This principle is important to consider when planning or evaluating new product launches. The role of incremental innovation and new product development have been highlighted in many publications as an avenue for company growth and survival (e.g. Cooper, 2005; Kleinschmidt and Cooper, 1991; Sorescu and Spanjol, 2008). Whilst responding to market trends is important, the importance of core products in the portfolio may be overlooked if the company overly focuses on new products. Core products are important in bringing buyers to the brand, however quantifying this importance – in terms of buyer contribution – has not been well-documented in prior research. Understanding the role of core products (i.e., top-sellers) within the product portfolio is thus very important in how they contribute buyers and sales towards the brand (Taylor, 2012).

Accordingly, a gap in this body of work relates to how one can evaluate brand portfolio efficiency in terms of how each SKU or product variant attracts unique buyers and contributes sales/revenue; and whether there is an expected level of contribution of unique buyers and sales for each product in the portfolio. Furthermore, the impact of product portfolio size on overall brand penetration has not been the primary focus of research in portfolio management to date.

Solely relying on sales performance is inadequate as it ignores cannibalisation and the extent to which each product assists with

<table>
<thead>
<tr>
<th>Tool</th>
<th>Provider</th>
<th>Overview</th>
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<tbody>
<tr>
<td>JDA Assortment Optimization</td>
<td>JDA Software Group</td>
<td>• Assortment lifecycle planning, including sizing and pre-pack</td>
</tr>
<tr>
<td>Assortment Optimization</td>
<td>Nielsen</td>
<td>• Allows for assessment and adaption mid-season</td>
</tr>
<tr>
<td>Assortment Optimization</td>
<td>IRI</td>
<td>• Assess the incremental volume towards the segment and the category.</td>
</tr>
<tr>
<td>Assortment Planning</td>
<td>Manhattan Associates</td>
<td>• Includes proprietary shelf-space management software for optimal locations on the shelf and in the store.</td>
</tr>
<tr>
<td>Retail Assortment Planning</td>
<td>Oracle</td>
<td>• Assortment planning and product selections based on buyer preferences, local markets, cross-channel and space considerations.</td>
</tr>
<tr>
<td>Assortment Planning</td>
<td>Just Enough</td>
<td>• Demand forecasting, clustering, and optimization routines to allocate the assortment by size/prepacks.</td>
</tr>
<tr>
<td>TXT Retail Planning</td>
<td>Aptom</td>
<td>• Uses techniques such as clustering and profiling to automatically create assortment plans.</td>
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<tr>
<td>Assortment Planning for Retail</td>
<td>SAP</td>
<td>• Combines customer demographics with product attributes to suggest localised assortments.</td>
</tr>
<tr>
<td>daVinci Assortment solution</td>
<td>IFS</td>
<td>• Determine the assortment breadth and depth in line with goals.</td>
</tr>
<tr>
<td>SAS Integrated Merchandise Planning</td>
<td>SAS</td>
<td>• Analysis on demand quantities based on referenced historical data across product categories and selling locations.</td>
</tr>
<tr>
<td>Assortment Optimization</td>
<td>Precima</td>
<td>• Monitor underperforming items, and identifies best performing products.</td>
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