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

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

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. The results emphasise the importance of having top-selling SKUs readily available to the consumers, rather than sacrificing them for new product launches.

Key words: Brand management, portfolio size, portfolio composition, portfolio evaluation

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 (Mason and Milne, 1994); guarding valuable shelf-space and/or responding to demands from retailers (Sorensen, 2009; Hubner and Kuhn, 2012; Chimhundu et al., 2015). However, introducing new products to market is highly risky (Castellion and Markham, 2013; Martos-Partal, 2012) with high failure rates. 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 disproportionally 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 the different offers to 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; Srivastava, 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. 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*, *Shoecare*, *Soup*, *Vitamins*, and *Yogurt*). The US data is obtained from the IRI database (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 data description and the methods employed for the analysis, then the results are presented.

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 of the products is part of these monitoring activities – to ensure that 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).

Table 1 – Summary of Major Assortment Planning Tools

Tool	Provider	Overview
JDA Assortment Optimization	JDA Software Group	• Assortment lifecycle planning, including sizing and pre-pack • Allows for assessment and adaption mid-season
Assortment Optimization	Nielsen	• Assess the incremental volume towards the segment and the category. • Includes proprietary shelf-space management software for optimal locations on the shelf and in the store.
Assortment Optimization	IRI	• Assess the product value on a shelf, through attribute evaluation • Considers factors such as product interchangeability and cannibalisation
Assortment Planning	Manhattan Associates	• Assortment planning and product selections based on buyer preferences, local markets, cross-channel and space considerations.
Retail Assortment Planning	Oracle	• Demand forecasting, clustering, and optimisation routines to allocate the assortment by size/prepacks
Assortment Planning	JustEnough	• Uses techniques such as clustering and profiling to automatically create assortment plans
TXT Retail Planning	Aptos	• Combines customer demographics with product attributes to suggest localised assortments
Assortment Planning for Retail	SAP	• Determine the assortment breadth and depth in line with goals • Analysis on demand quantities based on referenced historical data across product categories and selling locations
daVinci Assortment solution	IFS	• Determine the ranges, sizes, colours, styles and mix for each store
SAS Integrated Merchandise Planning	SAS	• Anticipate customer demand and create plans. • Optimise assortments to meets demand for style, colour or size.
Assortment Optimization	Precima	• Monitors underperforming items, and identifies best performing products.

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 or 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:

$$b_{\mathrm{A|B}} = D \times b_{\mathrm{A}}$$

where $b_{\mathrm{A|B}}$ 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.

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 $C \in$ 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; Romaniuk 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 overall brand penetration. By looking at incremental penetration, we can measure portfolio efficiency in how each product contributes to the overall sales and buyers. This is also in line with the principle that brands grow mainly through gains in penetration (Sharp, 2010; Romaniuk et al., 2014; Binet and Field, 2007). Consequently, the focus of this paper is to examine product portfolios through the contribution of incremental buyers that each variant brings towards the brand (along with revenue and units sold contribution) across fifteen different product categories over multiple years. The link between product portfolio and penetration is implicitly inferred in several studies: product variety is said to increase product selection and thereby appeal to a wider and more diverse set of customers (Wan et al., 2012; Ho and Tang, 1998; Betancourt and Gautschi, 1990). From an overall brand perspective, product variants do appeal to various overlapping demographic segments (Trinh et al., 2009). However, the degree to which they contribute to the overall brand penetration has not been explored, and given penetration's importance to growth, the area requires more focus to ensure it gets the attention it deserves. In order to address this research gap, we analyse product category data using *Saturation Curve Analysis*, as detailed below.

2.1 Saturation Curve Analysis

When the SKUs within a brand portfolio are plotted against their overall revenue contribution, the data form a logarithmic curve (Fisher and Raman, 2010; Wan et al., 2012). The curve implies that the total brand revenue is not uniformly distributed across the items. There are best sellers that contribute a larger proportion of brand revenue and a typically a large number of poor revenue contributors. This pattern is called *"the big head"*, where a large portion of sales are generated from a small number of items, with the rest forming *"the long tail"* (Sorensen, 2009). The Saturation Curve Analysis described here is grounded in a technique that has been applied to various disciplines from physics to economics, such as *Reed's Saturation Curve* in economics, which links population growth and growth in demand (Reed, 1925).

Existing saturation curve applications are cumulatively (e.g. unit sales or revenue). We develop the Saturation Curve Analysis using penetration. The difference between the usage of market share or sales with penetration is that the former two applications are simply additive, whereas penetration is not – due to the varying proportion of the buyers of smaller items who also purchase the more popular items. This adaptation is in line with the principle behind *Duplication of Purchase Law* (Ehrenberg and Goodhardt, 1970; Ehrenberg et al., 2004) – that SKUs will share buyers in line with their size in the market, i.e. SKUs have greater buyer duplication with bigger SKUs than with smaller SKUs. Furthermore, light buyers tend to select the more popular offerings. This is called the *Natural Monopoly Effect*, i.e. popular items tend to ‘monopolise’ light users (McPhee, 1963). Consistent with these two theoretical bases, buyers who purchase multiple SKUs in a brand portfolio will be apportioned as buyers of the biggest SKU in their repertoire (within the same brand).

Knowing the SKUs that form the big head (i.e. those that contribute the most buyers and sales), as well as the SKUs that form the long tail (i.e. those that provide marginal sales and buyers contribution), is important. It helps to quantify the importance of SKUs that attract a considerable number of buyers and may help brand owners to redirect resources and energy to heavy-lifting SKUs whilst still supporting promising product innovations. Exploring the shape of the penetration and sales curve across brands, brand sizes, and product categories is also useful to form benchmarks for product portfolio management.

Therefore, the paper addresses these two research questions:

RQ1: How does the contribution from each SKU within the portfolio vary in terms of:

(a) Penetration; (b) Unit sales; and (c) Revenue?

RQ2: How do the patterns observed from RQ1 differ by:

(a) Portfolio size; (b) Product category?

The next part of the paper discusses the method and the data used.

3. Research Method

3.1 Method of analysis

Saturation Curve Analysis enables the evaluation of product portfolios as to how each SKU uniquely contributes towards brand penetration and market share. It measures the cumulative lift of unique buyers, by ranking the SKUs from biggest to the smallest contributor of unique buyers, whilst also observing the sales lift that each SKU brings. Buyers of multiple SKUs are assigned to the largest SKU in their repertoire, in line with the *Duplication of Purchase Law* and *Natural Monopoly Effect*. The results of the analysis provide multiple insights into:

- the degree to which each SKU contributes to the brand's penetration and market share;
- how the saturation curve differs for competing brands, brand sizes, and product categories.

Whilst cumulative sales (value and units) for the product variants (top-*n*) within the portfolio are calculated by adding the figures together, the calculation for cumulative penetration for a brand's top-*n* SKUs can be mathematically displayed as follows (after the SKUs are ranked in order of the size of the buyers who purchased the SKU):

$$CumulativePenetration_n = \begin{cases} SKUBuyers_i, & i = 1 \\ \bigcup_{i=1}^{n} (SKUBuyers_i \cap CumulativePenetration_{i-1})^{-1}, & i > 1 \end{cases}$$

The results present the saturation rate for penetration and sales across the SKUs. For example, the 1st SKU contributes *x%* of the total buyers, *y%* of total units sold and *z%* of total revenue. The algorithm of the data analysis is included as **Figure A** in the appendix. As well as looking into the contribution of the top-selling SKU, the study also looks into the relative position of the SKU in the portfolio. The SKUs can be grouped into deciles, quartiles, or thirds to allow comparisons across portfolios of different sizes. For this study, the SKUs are grouped into quartiles, to see the contribution of each quartile to the total brand penetration and sales. The approach involves annotating the position of the SKU within the brand (e.g. for a brand with 10 SKUs: 1/10, 2/10, … 10/10) after they are ranked by its *unique penetration contribution*. For example, for a brand with four SKUs, the top-selling SKU is positioned in the first quartile and the smallest SKU is designated to the fourth quartile. The SKUs in the fourth quartile are expected to reach 100% cumulative brand penetration and market share. Next, an ANOVA (Analysis of Variance) is used to explore differences in the SKU contribution patterns across brand sizes and product categories to identify potential boundaries and the generalisability of the findings.

3.2 Data

We analyse data sets consisting of 13,681 brands and 92,877 SKUs across 15 product categories in the UK and US over multiple years (2004 -2006 in the US for *Shampoo* and *Frozen Pizza,* 2010 – 2013 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*, *Shoecare*, *Soup*, *Vitamins*, and *Yogurt*). Kantar Worldpanel provided the data for the UK product categories, whereas US data is sourced from the IRI database (Bronnenberg et al., 2008) and the Nielsen datasets at the Kilts Center for Marketing. In each case the data cover three years.

Each data set contains the number of units, price and the product purchased by the household panel, including other relevant information such as the manufacturer, pack size and features specific to the product category. This allows us to aggregate the information so that we have the number of SKUs for each brand, who buys them and the cumulative sales resulting from each SKU per year. The information about which brand the SKUs belong to, the households that purchased the SKUs, the total units purchased, as well as total sales, enable us to create a Saturation Curve for each brand using the steps in **Figure A** of the appendix.

Brands are distinguished through the separate ranges that are released by the manufacturers. For example, within *Shampoo*, distinct brands from *Unilever* in 2006 were: *Dove*, *Dove Advanced Care Therapy*, *Salon Selectives Full of It*, *Suave*, *Suave for Men*, *Suave Naturals*, *Suave Professionals*, *Sunsilk Straighten Up*, and *Thermasilk*. Although ranges with similar brand names can be aggregated further, these may cause separate ranges to come under a banner brand that may not reflect the true nature of the ranges due to their different positioning (e.g. budget vs. premium private labels).

4. Results

We start with descriptive results across the product categories and the brand portfolio sizes within each category. **Table 2** shows that there are different norms of the portfolio size by product category, with an average of 2 SKUs for an *Ice* brand, in contrast to the average of 16 SKUs for a brand of *Dry Cat Food*. The table also shows the proliferation of brands and SKUs in product categories such as *Beer* and *Vitamins* over the three years, compared to other product categories where the figures are relatively constant.

A closer look at the brands and their portfolio size within each product category reveals a skew towards brand with smaller portfolio sizes (as shown by the comparatively smaller Median to the Average) – as shown in **Table 3**. Similar patterns are also evident for Penetration, and Market Share, suggesting the abundance of small brands competing against market performers. This is also confirmed with correlation results. Portfolio size is strongly positively correlated with penetration and market share (with Penetration: 0.72; Market Share (Units): 0.63; and Market Share (Revenue): 0.64). All correlations are significant at

$p < 0.001$. Whilst there are big brands with few SKUs in the portfolio or vice versa, small brands typically have fewer products, and bigger brands provide more options for their consumers.

Table 2: Dataset descriptives

Country	Product Category	Year	# of brands	# of SKUs	Avg. portfolio size
US	**Beer**	2012	961	4745	5
		2013	1122	5422	
		2014	1161	5715	
	Deodorants	2012	143	1730	12
		2013	147	1731	
		2014	134	1621	
	Detergents	2012	205	2479	12
		2013	215	2485	
		2014	205	2455	
	Frozen Baked Goods	2012	312	1288	4
		2013	312	1288	
		2014	332	1325	
	Frozen Pizza	2004	49	418	9
		2005	48	424	
		2006	46	413	
	Gum	2012	145	1350	10
		2013	134	1332	
		2014	129	1277	
	Ice	2012	156	362	2
		2013	141	342	
		2014	149	345	
	Jam, Jellies, Spreads	2012	587	2849	5
		2013	615	3017	
		2014	640	3096	
	Shampoo	2004	104	659	7
		2005	101	695	
		2006	110	801	
	Shoecare	2012	69	651	9
		2013	83	657	
		2014	73	614	
	Soup	2012	441	2889	7
		2013	451	2891	
		2014	452	2958	
	Vitamins	2012	916	6988	8
		2013	950	7273	
		2014	1022	7522	
	Yogurt	2012	200	2266	12
		2013	198	2421	
		2014	198	2635	
UK	**Dry Cat Food**	2010	31	550	16
		2011	32	600	
		2012	31	386	
	Dry Dog Food	2010	48	750	15
		2011	45	721	
		2012	38	441	

Table 3: Portfolio Size and Brand Performance Descriptives

Product Category	Average # SKUs			Average Brand Penetration			Average Market Share (Units)			Average Market Share (Revenue)		
	Avg	*SD*	*Med*	*Avg*	*SD*	*Med*	*Avg*	*SD*	*Med*	*Avg*	*SD*	*Med*
Dry Cat Food	16.3	17.0	8	5.4	9.0	1.4	3.1	6.2	0.4	3.1	5.9	0.5
Dry Dog Food	15.4	17.0	9	2.9	5.0	0.8	2.2	4.6	0.4	2.2	4.6	0.6
Yogurt	12.3	28.9	4	1.2	6.5	0.0	0.4	2.8	0.0	0.4	2.8	0.0
Deodorants	12.0	27.8	2	1.5	4.3	0.0	0.7	2.1	0.0	0.7	2.2	0.0
Detergents	11.9	24.6	3	1.8	5.5	0.0	0.4	1.5	0.0	0.4	1.5	0.0
Gum	9.7	38.5	2	1.3	7.5	0.0	0.7	5.0	0.0	0.7	5.1	0.0
Frozen Pizza	8.8	10.9	4	6.4	8.8	1.8	1.9	3.5	0.3	1.9	3.6	0.3
Shoecare	8.5	26.0	1	1.5	8.4	0.1	1.3	7.7	0.1	1.3	7.9	0.1
Vitamins	7.5	21.5	2	0.2	0.9	0.0	0.1	0.2	0.0	0.1	0.2	0.0
Shampoo	6.8	11.3	2	2.0	4.4	0.2	0.9	2.4	0.1	0.9	2.3	0.1
Soup	6.5	19.3	2	0.8	5.0	0.0	0.2	1.9	0.0	0.2	1.9	0.0
Beer	4.9	9.0	2	0.2	1.3	0.0	0.1	0.6	0.0	0.1	0.7	0.0
Jam, Jellies, Spreads	4.9	8.5	2	0.4	2.6	0.0	0.1	0.9	0.0	0.1	1.0	0.0
Frozen Baked Goods	4.1	7.0	2	0.7	2.8	0.0	0.3	1.1	0.0	0.3	1.2	0.0
Ice	2.4	7.1	1	0.8	4.0	0.1	0.7	3.2	0.0	0.7	3.3	0.0
TOTAL	**6.8**	**18.1**	**2**	**0.7**	**3.8**	**0.0**	**0.3**	**2.0**	**0.0**	**0.3**	**2.1**	**0.0**

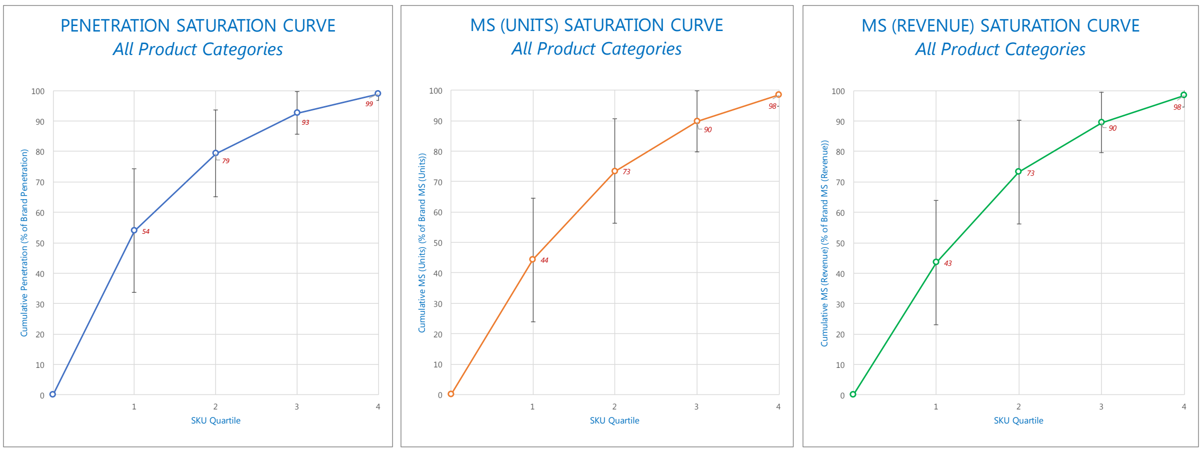
Using the algorithm described in **Figure A** in the appendix, the main analysis investigates each brand to see the pattern of contribution from the individual SKU to the overall brand penetration and market share. For the analysis, all of the datasets across the three years were aggregated. *Saturation Curve Analysis* results enable us to see the contribution patterns across the portfolio, with the results shown in **Table 4**. Regardless of product categories and brand sizes, the study shows that half of the SKUs are responsible for attracting 79% of brand buyers and contributing 73% of sales (in units and revenue), on average *(RQ1a, b, c)*. The magnitude of the contribution also informs brand owners of the importance to ensure that core products in the portfolio are available and well-distributed across all retail outlets.

Table 4: SKU Contribution Quartile towards Total Brand

Quartile	Avg. Cumulative Penetration	StDev	Avg. Cumulative MS (Units)	StDev	Avg. Cumulative MS (Revenue)	StDev
First	54	*20*	44	*20*	43	*20*
Second	79	*14*	73	*17*	73	*17*
Third	93	*7*	90	*10*	90	*10*
Fourth	99	*2*	98	*4*	98	*4*

The figures are plotted on to charts (**Figure 1**), displaying the convex relationship between SKU quartile contribution towards the total brand. The results show that the first portfolio quartile is expected to be purchased by over half of brand buyers (54%), while contributing around 44% of the total units sold for the brand and 43% of the total brand revenue. Half of the SKUs within a product portfolio across the categories typically contribute eight out of ten brand buyers, and nearly three-quarters of the units sold and brand revenue.

Figure 1: Penetration and Market Share Saturation Curves by SKU Quartiles



The next analysis looks at the contribution of the top-selling SKU towards total brand penetration and market share, regardless of brand size, as shown in **Table 5**. Single SKU brands were excluded for the obvious reason that the SKU contributes to 100% of the penetration and sales.

Table 5: Top-selling SKU Contribution towards Total Brand – By Product Category

Product Category	% of Brand Penetration		% of Brand Market Share (Unit)		% of Brand Market Share (Revenue)	
	Average	StDev	Average	StDev	Average	StDev
Ice	67	*16*	63	*22*	59	*24*
Frozen Baked Goods	53	*19*	49	*22*	49	*23*
Gum	52	*21*	49	*25*	47	*27*
Soup	50	*19*	45	*22*	45	*23*
Vitamins	49	*23*	46	*26*	45	*27*
Jam, Jellies, Spreads	48	*19*	45	*22*	44	*23*
Beer	48	*18*	42	*26*	45	*24*
Frozen Pizza	48	*19*	38	*23*	38	*23*
Detergents	47	*21*	45	*24*	42	*25*
Deodorants	46	*23*	44	*25*	43	*25*
Shoecare	42	*24*	39	*24*	42	*26*
Yogurt	41	*18*	33	*24*	33	*24*
Shampoo	41	*20*	37	*21*	38	*22*
Dry Dog Food	38	*21*	33	*22*	29	*24*
Dry Cat Food	37	*20*	29	*22*	26	*23*
Average	**48**	***20***	**44**	***24***	**44**	***25***

The top-selling SKU typically contributes around half of brand buyers, ranging from 67% for *Ice* to 37% for *Dry Cat* Food. Top-sellers also bring more than 40% of the brand sales, with the value ranging from 29% *(Dry Cat Food)* to 63% *(Ice)* for unit sales, and 26% to 59% with *Dry Cat Food* and *Ice* also at the opposites of the spectrum.

Several one-way analyses of variance (ANOVA) were conducted to verify the differences in penetration, brand unit share and brand revenue share that were statistically significant across the categories. We used one year data subsets for this analysis to avoid dependencies within the items that would occur if multiple years were used together. Results were: Year 1: *Penetration:* $F(14,2647) = 10.14$, $p < 0.001$; *Market Share (Units):* $F(14,2647) = 9.13$, $p < 0.001$; *Market Share (Revenue):* $F(14,2647) = 7.38$, $p < 0.001$. Year 2: *Penetration:* $F(14,2766) = 8.06$, $p < 0.001$; *Market Share (Units):* $F(14,2766) = 8.56$, $p < 0.001$; *Market*

Share (Revenue): F(14,2766) = 7.19, $p<0.001$. Year 3: *Penetration:* F(14,2849) = 8.38, $p < 0.001$; *Market Share (Units):* F(14,2849) = 8.97, $p < 0.001$; F(14,2849) = 8.31, $p < 0.001$.. The results indicate there are statistically significant differences in top-SKU's contribution to the brand's penetration and sales, by product category. Note that some of the product categories have differing sample sizes and unequal variances, violating several ANOVA assumptions. However, ANOVA is quite robust to these problems (Hair et al., 1998 ch. 6). Also, the violations of these assumptions are not necessarily a serious shortcoming for this study because they primarily influence the probability of Type 1 errors (Glass et al., 1972). The p-values from our overall ANOVA are significant at the 0.001 level, which makes it less likely we are finding false positive results. With wide ranging differences in average penetration and market share for the top selling SKU as shown in **Table 5**, posthoc analysis using Tukey's range test reveals four to six homogeneous subsets of categories with similar penetration and market share averages.

Looking into different portfolio sizes (regardless of product categories), there is naturally a stronger contribution for the top-selling SKU for brands with fewer SKUs in their portfolio. **Table 6** shows that for brands with two to three SKU, the biggest SKU brings on average six out of ten brand buyers and 60% of the sales. Even for brands with 11 SKUs or more, the top-selling SKU is still expected to bring close to three out of ten brand buyers and 20% of the total sales *(RQ 2a, b, c)*. Several One-way ANOVA analyses were conducted on the results again using single-year data subsets. Results were: Year 1: *Penetration:* F(3,2658) = 1002.65, $p < 0.001$; *Market Share (Units):* F(3,2658) = 679.11, $p < 0.001$; *Market Share (Revenue):* F(3,2658) = 661.64, $p < 0.001$; Year 2: *Penetration:* F(3,2777) = 949.52, $p < 0.001$; *Market Share (Units):* F(3,2777) = 694.03, $p < 0.001$; *Market Share (Revenue):* F(3,2777) = 682.10, $p < 0.001$; Year 3: *Penetration:* F(3,2860) = 955.01, $p < 0.001$; *Market Share (Units):* F(3,2860) = 627.28, $p < 0.001$; *Market Share (Revenue):* F(3, 2860) = 580.32,

$p < 0.01$. The results confirm there are statistically significant differences in the top-selling SKU's contribution when compared across portfolio sizes, and that they persist across multiple years. Post-hoc Tukey range results suggest the existence of four homogeneous subsets that correspond to the portfolio size grouping as displayed in **Table 6**.

Table 6: Top-selling SKU Contribution towards Total Brand – By Portfolio Size

Number of SKUs in Brand	% of Brand Penetration		% of Brand Market Share (Unit)		% of Brand Market Share (Revenue)	
	Average	StDev	Average	StDev	Average	StDev
2 – 3	63	*15*	60	*21*	60	*22*
4 – 5	48	*15*	43	*19*	43	*20*
6 – 10	40	*14*	34	*17*	35	*18*
11+	26	*12*	20	*13*	20	*14*
Average	**48**	***20***	**44**	***24***	**44**	***25***

The results further emphasise the importance of the top-selling SKU, especially for brands with smaller portfolio sizes (that are more likely to be small brands). Focusing on innovation or additional products at the expense of the core products potentially jeopardises a large portion of brand buyers and sales.

5. Discussion and Conclusions

There were two principal objectives of this study. First, to explore the contribution of each SKU / product within a portfolio towards the total brand penetration and market share across brands in fifteen categories. The results provide norms for brand owners on the important role of their core products which are vital to consider in decision-making such as related to new product launches and resourcing. Second, was to provide a simple and transparent method to quantify the buyer and sales contribution from each of the SKU within the portfolio, by adapting two existing methods, saturation curve and *Duplication of Purchase* Analysis.

The descriptive analysis delivers two important observations. First, we find that portfolio size is category specific. This means that each category has different portfolio norms and understanding them should guide portfolio decisions. The ongoing discussion in the literature in regards to product innovation and whether providing more or fewer options for consumers is better (Scheibehenne, 2008; Scheibehenne et al., 2010) should be focused on the conditions under which they lead to higher sales and more buyers from manufacturer and retailer perspective.

Second, our findings confirm the importance of the largest SKUs (i.e. the core products) in the portfolios of brands (Taylor, 2012). Although the figures vary across categories and across portfolio sizes, top-selling SKU contributes up to half of total brand buyers and 40% of the brand sales on average. This quantifies the importance of the top-selling SKU and 'core' product to brand portfolios. The rest of the SKUs in the portfolio contribute buyers and sales at a diminishing rate. This is in line with consumer behaviour knowledge as seen in the *Duplication of Purchase Law*, where buyers of smaller brands / SKUs are also more likely to purchase the bigger brands / SKUs (Ehrenberg et al., 2004) as well as *Natural Monopoly Effect*, where consumers gravitate towards popular brands or items (McPhee, 1963). This finding confirms that it is critically important for brand owners and retailers to have the top-selling SKUs on shelves and widely distributed across channels. The resources spent on product innovation should not be at the expense of ensuring that core products are well-distributed and adequately resourced across retail outlets.

The other main contribution from this study was the development of a method - ***Saturation Curve Analysis*** to assess SKU buyer and sales contribution towards the brand. The method is transparent and relies of easily available data, which provides marketers with a tool to evaluate their product portfolio without relying on proprietary or 'black-box' algorithms. This method complements *Duplication of Purchase* analysis – where the degree of duplication or cannibalisation is reported – by providing the degree to which each SKU contributes incremental penetration towards the portfolio. With the availability of data for competing brands across the market, researchers and brand owners can build the saturation patterns as the norm for the product category, against which the pattern for brand portfolios can be compared. Furthermore, researchers can observe commonalities or differences across the saturation patterns for competing brands, as well as different product categories.

The saturation patterns explored in the paper provide norms of how each product is expected to contribute towards the total portfolio. This provides an opportunity for brand owners to investigate whether the rest of the products address category needs sufficiently, or if there is issue in product distribution for the rest of the products in the portfolio.

In summary, this paper provides contributions to category management for academia and industry – adding to the body of knowledge on the role of core products as the heroes in the product portfolio on how they contribute buyers and sales towards the brand, and providing ancillary findings to help drive further research into product portfolio management.

5.1 Limitations and Future Research

The paper evaluated 13 consumer packaged goods product categories from the United States and two from the United Kingdom. As such, an ideal research extension may involve other product categories such as durables or services (e.g. financial services, education). Further replications and extensions across different countries would also be beneficial to evaluate whether similar relationships between portfolio size and the dependent variables exist, and the portfolio composition (e.g. the numbers of scents, flavours or sizes) that are related to brand growth. Future research may also seek and explore factors behind the product category differences, such as hedonic vs. utilitarian product categories.

Future research with a longer observation period may also benefit from the application of other approaches such as the Fixed Effects Model – exploring the association between portfolio characteristics and the dependent variables, and how changes to these characteristics over time on the same brand cohorts relate to the changes in penetration and market shares. Longer observation periods may also uncover factors that influence the stability or changes in how each SKU contributes to total brand performance. Subsequent studies should also consider external factors such as economic growth as well as growing or declining categories, as these factors may also affect how top-selling SKUs contribute buyers and sales to the brand.

The study did not take profitability into consideration. The inclusion of product and portfolio profitability for future research will provide a clearer picture of the factors that influence brand owners to offer or retain products that may be performing poorly in attracting buyers and sales, but with high profit margin.

Further research that also stems out of the analysis is to examine the *specific value of the portfolio element* that contributes the most for brand growth. For example: certain flavours, scents or other specific features, that can be associated with higher penetration and market share across competing brands.

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Appendix

Figure A - *Saturation Curve Analysis* algorithm

```
For each brand B (i = 1 to n) do
   Initialise Cumulative Penetration (CP) = 0,
   Cumulative Revenue (CR) = 0,
   Cumulative Units (CU) = 0

   Sort all SKUs by the order of penetration p

   For each B.p (j = 1 to n) do
      If j = 1 then                       // j = 1 is the biggest SKU
         Set CPj = the number of buyers for Bi.pj
      Else
         Select buyers(Bi.pj) not currently included in CPj
         Set CPj = Cpj-1 + incremental Buyers(Bi.pj)
      End-if
      Set CRj = CRj-1 + Sales(Bi.pj)       // Revenue for Bi.pj
      Set CUj = CUj-1 + Units(Bi.pj)       // Units sold for Bi.pj
   End-for
End-for
```

Note: The outer loop recursively cycles through the brands in the market, and is not needed when the algorithm is used to analyse a single brand portfolio. The inner loop goes through each SKU in the brand portfolio and measures its buyer and sales contribution towards the brand portfolio.

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