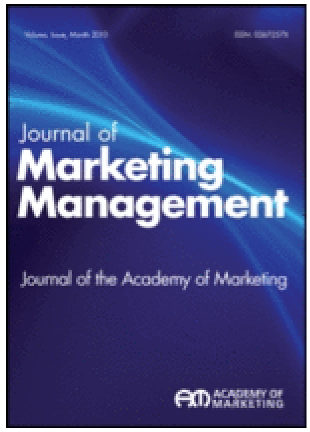

The Unbearable Lightness of Buying

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The Unbearable Lightness of Buying

Abstract

Although marketers are increasingly asked to manage brands for the long-term, it is difficult to do so when no clear picture exists of long-term brand buying. This study reports cumulative behavioural loyalty outcomes for 200 UK consumer-goods brands when observed in a five-year household panel of continuous reporters. We examine these brands in intervals from one to five years against NBD (Negative Binomial Distribution)-model projections. Stationary brands attract over twice as many buyers in five years as they do in one. Of these buyers, 80% purchase the brand at a rate of once a year or less, yet contribute 40% to total sales, a Pareto ratio of just 60:20. For managers, this light buying is broadly predictable from NBD fittings to annual data, and implies a renewed emphasis on nudging the brand buying propensities of the whole market.

Summary Statement of Contribution

Few studies have considered brand performance cumulatively. We present new benchmarks for the developments not easily seen in annual panel data, that occur in the buyer base of stable consumer packaged goods brands over five years. These include continuing cumulative penetration growth, and a large influx of light buyers. We advance NBD theory, demonstrating how a stochastic model can still explain and project these changes from annual fittings, to link the 'here and now' with long term brand performance.

Keywords: brand performance, brand loyalty, heavy buyers, NBD buying, long-run marketing objectives, Pareto share

Introduction

Many studies have examined the preponderance and sales contribution of light and heavy buyers in repeat-purchase categories, such as coffee, cereal or toothpaste. The general out-take of their findings is that (a) the heavy-half of a category's buyer base contributes approximately 80% of sales; and (b) brands invariably have many more 'light' or infrequent buyers, and far fewer medium and heavy buyers. Substantial research, largely conducted from a few quarters of panel data, has been devoted to examining the behaviour and value of the brand's heaviest buyers (e.g. Hallberg, 1995; Hallberg, 1999; Koschmann & Sheth, 2018; Reilly & Rapacz Deb, 2009; Romaniuk & Wight, 2015), but far fewer studies report on the loyalty and sales contribution of the lightest.

Sharp (2010) reports that in one year light brand buyers account for approximately 50% of brand sales. However, the further sales contribution of these buyers to total longer-run revenues, and their role in the customer base relative to heavier buyers, is still little understood. More comprehensive knowledge on this issue is desirable since it is increasingly recognized that brands are built slowly (Thomas & Kohli, 2009) and should be managed with a long-term perspective (Lodish & Mela, 2007).

Therefore, in this study we describe the repeat-buying behaviour and sales contribution not of the heaviest, but of the *lightest* brand buyers, those who continue to buy the category over an extended period, even if they only intermittently buy the focal brand. Our main interest is in understanding their contribution to long-run stable brand performance over a five-year business-planning cycle (Valentin, 2014; Webb, 2019) since, in consumer-packaged goods (CPG) markets, this is a normal outcome for almost eight in ten brands (e.g. Dekimpe & Hanssens, 1995a).

Brand growth, when it does occur, is driven by persistent penetration increases in successive *equal-length* management periods (Ehrenberg et al., 2004; Kennedy & Hartnett, 2018; Sharp, 2010). In other words, a growing brand has more households buying it in each month, quarter or year. We distinguish this use of the word 'growth' from the fact that brand penetration (Ehrenberg, 2000) is a time-dependent metric that grows (gets larger) as we look over longer time periods. That is, even brands that remain stable from quarter to quarter in terms of sales *accumulate* buyers steadily over successively longer periods. Their total buyer base is larger in six months than a quarter, and substantially larger again when measured over a year.

Cumulative penetration growth occurs because many brand buyers have long interpurchase cycles. They do not buy in every quarter and may not even return to the same brand in the same year. This cumulative view of brand buying in successively longer management periods is informative. Significant changes occur in the composition and average purchasing incidence of the buyer base of stationary brands, knowledge that led to the development of empirical generalisations in repeat-buying (East & Ang, 2017), and the discovery of their close fit to the NBD or Negative Binomial Distribution over the course of a few quarters (Ehrenberg, 1959; Morrison & Schmittlein, 1988).

The NBD describes the distribution of fixed purchase probabilities over a population of heterogeneous buyers. In one, or over successive periods, it then predicts the proportion and sales contributions of light and heavy buyers in the customer base; the repeat and attraction rates; and cumulative penetration growth necessary to maintain brand share. A fundamental finding is that the distribution of light and heavy buying varies little between competing brands (Dawes & Trinh, 2017). This finding emphasises a marketing imperative beyond simply targeting the heavy half, for example the importance of maintaining the size of the entire customer base and managing the sales contribution of the brand's lightest buyers–particularly the large numbers that move from zero to one and from one to zero purchases in successive periods (Romaniuk, 2011).

But the NBD (and similar stochastic models) share a limitation. Even though stationarity is the observed norm, they have seldom been applied to continuous buying over periods of more than a year or two (e.g. East & Hammond, 1996), or then only in limited cases (e.g. McCarthy et al., 2017; Stern & Hammond, 2004). If the stationarity assumption is met, the NBD will project even the lightest buying expected to manifest in any future period, including in a five-year planning window, although little data has yet been available to test this.

Our aim in this study is therefore two-fold; first to establish in many sets of data the norms for buyer composition and behaviour in the long-run buyer base, and second to determine the ability of the NBD to predict those regularities. Successful estimates of long-term outcomes from short term data will extend theory and offer a new managerial tool to set realistic long-run brand objectives. We therefore ask (1) by how much does the customer base grow (i.e. accumulate) between one and five years? At that point, (2) what proportion of light buyers does it generally contain; (3) what is the sales contribution from those buyers; and (4) what proportion of the buyers in any year did not buy the year before. Finally, we ask (5) how closely these changes in cumulative performance are predicted from an annual NBD fitting.

We derive a five-year panel of continuous reporters from standard panel data to observe the cumulative customer bases of 200 competing brands in 10 UK categories. Since standard panels use a sample with replacement, this is a necessary step to capture comprehensively the preponderance, sales contribution and predictability of light buying. We then propose several novel empirical generalisations which we assess against their theoretical NBD benchmarks.

We find that even with stable market share, the average brand customer base is twice the size in five years that it is in one, and continues to be characterised by extremely light buying. Typically, four in ten customers buy *just once* in five years; and about eight in ten make five purchases or fewer in the same time. But, as light as these buyers are, they contribute together almost 40% of total brand sales, a generalised Pareto share of just 60:20. In addition, in each and every year, two in every five brand buyers do not buy that brand in the previous year; a useful annual target. And last, for any brand that maintains the same *annual* penetration level, we find that the NBD can be extended from its one-year fitting to provide close benchmarks for these and other regularities in the five-year planning frame. Repeat-purchase loyalty is critical for CPG brand performance (e.g. Uncles & Ellis, 1989); these findings focus attention on the surprisingly under-reported loyalty of extremely infrequent buyers - what we call the 'unbearable lightness of buying'.

The paper proceeds as follows. In the next section we discuss prior work on the distribution of buying frequencies, and the theoretical models we apply. We then describe our method, before presenting the findings, concluding with a discussion of their implications for theory and practice.

Background and Literature Review

We start by reviewing relevant work on the different rates at which consumer households buy product categories. This literature is the basis for subsequent work on brand buying rates, in particular of the lightest buyers, which are the focus of this study.

Light and Heavy Category Buyers

Authors have long made a distinction between light and heavy buyers of a product category and endeavoured to draw marketing implications from the difference. Twedt (1964) was the first to write about the sales appeal of the heavy category buyer – *'if another household were to consume 30 six-packs ….. that household should be 30 times as important as those represented by the household that buys only one …'* (1964 P. 71). Twedt examined the proportion of product purchases bought by the lightest 50% of buyers and the heaviest 50% of buyers. He found the heavy half accounted for about nine times the sales volume of the lightest half. Cook and Mindak (1984) replicated Twedt's study twenty years later and found virtually the same result. Romaniuk & Wight (2015) extended these findings to the top 20% of heavy buyers and found they accounted for 55% of total category purchases. Therefore, there is a robust finding that the heavy category buyers account for significant category purchases in a time period of 12 months.

Distribution of inter-purchase times and buying frequencies for categories

Several studies progressed from the idea of a heavy-light dichotomy and examined more fully the *distribution* of purchase frequency or inter-purchase time for product categories. By distribution, we mean the relative incidence of each number of purchases or purchase times, exhibited in a sample of households. Ehrenberg (1959) was the first to show that the number of households buying a category on 1,2,3 … *n* occasions in a fixed time such as a year follows a Negative Binomial Distribution or 'NBD'. This distribution typically takes an inverse J shape with a large peak at the 'light' end of the buying frequency spectrum. We provide additional technical detail of the NBD in a later section.

Another stream of purchase research began in the 1980s relating to the distribution of inter-purchase times for product categories (e.g., Jeuland, Bass & Wright, 1980; Morrison and Schmittlein, 1988). Inter-purchase time is simply the time analogue of purchase frequency: if a household purchases a category once per year its inter-purchase time in that period is 52 weeks. The Poisson assumption of the NBD model implied that inter-purchase times for product categories follow the exponential distribution (Chatfield & Goodhardt, 1973). The principal result was the same as the earlier work on purchase incidence: the majority of buyers in consumer goods categories buy that category quite infrequently in six months or even in a year.

Distribution of interpurchase times and buying frequencies for brands

Chatfield, Ehrenberg and Goodhardt (1966) extended the NBD patterns found in analyses of category purchase to brand buying. They showed various examples of brand purchasing that followed the NBD or related LSD (log series) pattern. Other examples of brands exhibiting NBD-like patterns of purchase frequency have been documented since (e.g. Dawes, 2016).

Another well-known generalised model of the original NBD model is the Pareto-NBD model. Schmittlein et al. (1987) argued that the Poisson distribution only accounts for active customers. "Death" or "drop out" customers are not Poisson distributed, rather, they follow the Pareto distribution (Johnson & Kotz, 1970). The Pareto/NBD is highly regarded for customer base analysis in the marketing literature. Recently, many researchers have extended this model in different areas (Abe, 2009; Batislam et al., 2007; Bemmaor & Glady, 2012; Fader et al., 2005; Jerath et al., 2011; Reinartz & Kumar, 2003). For example, Fader et al. (2005) developed a new model, the beta-geometric/NBD (BG/NBD), which is easier to implement than the Pareto/NBD model. Batislam et al. (2007) modified the BG/NBD model to the MBG/NBD model which allowed customers drop out at time zero (immediately after the first purchase). Abe (2009) extended the Pareto/NBD model using a hierarchical Bayesian (HB) framework to focus on customised marketing. Bemmaor and Glady (2012) proposed to replace the Pareto distribution with a gamma mixing of Gompertz distributions (G/G), which allows for the probability density function to be skewed to the right or to the left; and its mode can be at zero or shift away from zero. A non-zero mode might occur when the organisation offers strong differentiation and has a strong reputation, such as high-end hotels and up-scale catalog retailers (Bemmaor and Glady, 2012).

The Pareto/NBD model is proposed for organisations that have information on initial purchases and former customers who are no longer active. Some examples are catalogue mailing lists, church directories, dentist and beauty salons' files, department store charge card records, and triers of a new grocery product (Schmittlein et al., 1987). At the brand level, the Pareto/NBD has some potential for monitoring sales of a newly introduced brand, but is not recommended for established brands in markets such as FMCGs (Morrison & Schmittlein, 1988). The reason is that, for a mature brand, it is difficult to identify when a consumer made the initial purchase of the brand. For example, it is difficult for Colgate to identify when a given consumer made their first ever purchase. It is also difficult to identify if a given consumer is permanently inactive unless the consumer is literally dead. A consumer might have not bought Colgate for months or years but there is still a probability that the consumer will buy Colgate again in the future.

East & Ang (2017) describe how subsequent work then built on the NBD to show that multi-brand buying could be reliably modelled using what has become known as the NBD-Dirichlet (Ehrenberg et al., 2004). Numerous studies have demonstrated that a wide variety of performance metrics for competing brands including penetration, average buying rate and share of category requirement (SCR) can be predicted simultaneously by calibrating the model from just a few inputs - category penetration and buying rate; and competing brand shares.

The fact that brand buying frequencies can be accurately estimated using only category buying rates and brand market share as inputs has an important implication. It is that the proportions of heavy and light brand buyers in the brand customer base are quite predictable and are largely a function of brand size. Despite this regularity, the appeal of heavy brand buyers has been regularly highlighted (Hallberg, 1995; Hallberg, 1999; Reilly & Rapacz Deb, 2009; Shaw & Mazur, 1997) and yet, while by definition heavy brand buyers are monetarily more valuable per capita than light buyers, the widespread fit of the NBD-Dirichlet and the earlier NBD suggests brands are not able to selectively attract heavy buyers to any greater extent than their competitors. Hence management should be equally concerned about maintaining the numbers and purchasing rates of their lightest buyers, and continually attract them back to the brand.

It is a requirement of stochastic models such as the NBD that the categories and brands examined should be stationary (e.g. Goodhardt et al., 1984). For brands, this means that their market share is stable (but can temporarily fluctuate) over the time period of analysis (Dekimpe & Hanssens, 1995a). Many studies show that the majority of established brands do indeed have fairly stationary market shares over time periods extending from one to several years (Bronnenberg et al., 2012; Graham, 2009). The concept of stationarity is important for the next two pieces of knowledge that have emerged from this field, namely the apparent phenomena of 'loyalty loss'; and the notion of *cumulatively growing* brand penetration over successively longer intervals.

Apparent loyalty loss and conditional expectations of future purchasing rates

Earlier we highlighted the incidence and sales contribution of heavy brand buyers. From time to time in the popular press, writers have discussed the idea that brands 'lose' these heavy buyers over time. For example, Pointer Media Network and the CMO Council (2009) reported (p.2):

> loyalty erosion and consumer defection are pervasive and costly problems for CPG brands …. for the average CPG brand in this study, only 48% of 'high loyal' consumers in 2007 remained highly loyal in 2008.

Unfortunately, concerns such as these confound an apparent loss in loyalty with what is merely a regression to the mean effect (Barnett et al., 2005). The effect is caused by misclassifying buyers as heavy, based on a single year's buying, at a rate which for any particular household varies randomly from year to year (Schmittlein et al., 1985). Importantly, the regression to the mean effect is closely predicted by the NBD (Morrison & Schmittlein, 1988). The NBD model takes inputs from an initial time period and produces 'conditional expectations' of mean purchase rates for the non, light, medium and heavy buyers in that first period to the next (Goodhardt & Ehrenberg, 1967; Lenk et al., 1993; Morrison, 1969). Its output therefore predicts the extent to which one year's heavy buyers become 'lighter' on average in the next. Importantly, it also shows that the reduction in sales from year-one heavy buyers who regress *down* to their long-run mean is made up by an increase in sales from households who did not buy the brand at all or bought it very lightly in year one, and who then regress *up* to their mean in year two.

In any time period there is a large pool of brand buyers available, but only some will buy in every successive one, therefore a brand's cumulative buyer base – even a *stationary* brand - will increase in size over successively longer time periods. There has been some limited documentation of this effect. Ehrenberg (2000) showed brand penetration increases, but at a diminishing rate over longer time periods. That is, a brand's penetration in one year tends to be larger than it is in one quarter, but not four times as large. For example, using the data from *Repeat-Buying* Table 3.1*a*, (Ehrenberg, 2000 p. 33) the average percentage increase in brand penetration from 12 to 24 weeks is 42%, but from 24 to 48 weeks is only 22%. Over a year, this accumulating penetration is also closely predicted by the NBD.

Cumulative penetration growth – even for stationary brands - occurs because brand-buying rates are highly heterogeneous. Therefore, as we observe two successive quarters, simply as a function of the cut off some light buyers who did not buy in the first will buy in the second, but some who bought in the first will not repeat in the second. Accordingly, the buyer base grows cumulatively, even when the brand is maintaining stable sales or market share in the aggregate.

Two important implications follow from this discussion. First, if a stable brand's customer base grows cumulatively over time, then the size of *any* brand's customer base is conditional on the time period. While this seems intuitively obvious, marketers and researchers very often use fixed time periods such as a quarter or a year for analysis, reporting and decision-making. While it is understandable to report and evaluate performance in this way using comparable fixed time periods, it is possible that doing so constrains knowledge about the eventual composition of a brand's total customer base. For example, a manager of a brand with 10% annual penetration might be forgiven for thinking that brand's customer base *only* comprises 10% of households. And indeed, it does if we consider customers to be only those who happened to purchase in the last 12 months; but it does ***not*** if we think longer-term. For a stationary brand with a 10% annual penetration, in each additional year the composition of its customer base will include more and lighter buyers. This accumulated enlargement of the buyer base would be small if there were only a few buyers with inter-purchase intervals longer than a year or so, but the question thus arises: by how much does a brand's cumulative customer base continue to grow over extended periods, say between one and five-years, two time frames commonly adopted for strategic business planning (e.g., Webb, 2019).

This question is of the essence for long-term planners, because if the brand's buyer base does not grow cumulatively by much at all, then managers have some justification for thinking their customer base comprises a finite proportion of the population. But if the brand's customer base continues to grow appreciably, then the established use of cross-sectional reporting periods, even time frames as long as a year, severely underestimates the real size of the customer base in the five-year planning window. Moreover, if there is substantial cumulative customer base growth then it suggests that a large proportion of that brand's total customer base hardly buy it at all from year to year. In turn this has implications for marketing planning questions such as the effective reach of brand communication. A very large proportion of a brand's buyer base might be *extremely* infrequent purchasers. As such, they have fragile brand memory structures (Heckler et al., 2014; Romaniuk & Sharp), and so the challenge for managers is to establish how widely purchase propensities must be nudged to maintain even a stable brand share. Extant literature continues to emphasise the importance of light buying to performance over the course of a year (e.g., Anesbury et al., 2020; Anschuetz, 2002), but if penetration continues to swell, the *cumulative* scale of that challenge has not yet been documented. Based on the preceding points the first research question is therefore:

RQ1. How much does the customer base of a stable brand grow in successively longer planning periods, for example from one year to five years?

If the brand's buyer base does grow cumulatively over time, as stated above it involves households who did not buy in one time period, for example year one, but did buy in year two. It might even comprise some households that did not buy in year one ***or*** two but bought in year three, and so on. Such households would be extremely infrequent or light buyers, and this prompts another question, namely, what proportion of the long-term customer base is this light? The reason this question is important is that it directly relates to many aspects of brand strategy. If an overwhelming proportion of brand buyers in say, five years are extremely light, marketing decisions on packaging and communications must be managed to reflect the very low levels of consumer knowledge in the total customer base that this implies (e.g. Simmonds et al., 2020; Vaughan et al., 2020).

Because it is not clear at present how much light buying might be expected as a result of continuing penetration growth over time, RQ2 is:

RQ2. What proportion of a brand's long-term buyer base is extremely 'light', i.e. buying on average once per year or less?

Pareto and how it depends on time periods

A further implication of cumulative penetration growth is that if heavy buyers from one period are 'lighter' on average in the next, the sales contribution of heavy buyers may diminish over periods longer than a year. Therefore, rules such as the 'heaviest X% buyers = 80% of sales' (e.g. Weinstein, 2002) may apply in annual time periods, but they may be quite different over longer periods.

A generalization often quoted in brand management is the Pareto share or ratio, the idea that 20% of buyers could contribute 80% of the results. There are some conflicting findings concerning this ratio. Alongside the observed regression to the mean buying rate, Schmittlein, Cooper and Morrison (1993) identified a number of factors that appear to confound the "true concentration" ratio in observed category buying data, including the unit of analysis, the category penetration, heterogeneity in purchase rate across the population and observation time. Sharp (2010 Ch. 4) later confirmed that the Pareto share is time-sensitive for brands as well as categories, and rises from 39% in a quarter to 50% in one year. Over six years Kim, Singh & Winer (2017) report a Pareto ratio of 73% for cumulative dollar sales to continuous panellists, but even here, still not 80:20. Apart from the unit of analysis, a further explanation for that inconsistency may be that it is observed in 22 of the largest US product categories, many with high annual frequencies (e.g. cigarettes, soft drinks, toilet tissue), whereas Sharp (2010) reports on a more widely dispersed sample.

A high category purchase rate, and longer observation time result in increased concentration for the same reason; there is simply more opportunity for the heaviest buyers to make further purchases (Schmittlein et al., 1993). In longer analysis frames, the Pareto share accounts both for the extent to which cumulative increases in heavy buying rates will regress closer to their long term mean, and also for the arrival of lighter buyers. Long term observations would thus address an issue that frustrated earlier modellers attempting to arrive at a "true concentration" figure; namely, distinguishing among zero-buyers in a short-term dataset between those who will never buy, "hardcore non-buyers," and those whose light purchase propensities have not yet manifested.

Marketers often allocate investment based on rule of thumb beliefs such as the Pareto share, so if the sales concentration over five years is systematically lower than expected, then allocation decisions in the annual and five-year strategic plans should be re-evaluated to reflect an increased emphasis on the attraction of lighter buyers. Further evidence of a "true" value contributed by the lightest buyers to long-run sales is required to establish this, and therefore:

RQ3. What is the sales contribution of extremely light buyers over a five-year period?

Our fourth research question flows from the observation that many consumers who purchased a brand (perhaps once, or many times) in one year do not buy it in the next. This observation suggests a leaky bucket - that is, that those buyers who do not repeat are 'lost for good'. The alternative explanation is that it only reflects the operation of repertoire choices on ongoing category purchasing - in other words, a buyer does not in reality desert a brand, but rather allocates 'always a share' to it (even if very close to zero) over time (Banelis et al., 2013).

Ehrenberg's repeat-buying theory suggests that non-repeating buyers are not lost but are part of a large pool of brand buyers, each with different but established propensities to buy. 'Business as usual' marketing investment appears to maintain those propensities because the NBD assumptions and robust evidence over a few successive quarters show that loss and attraction will remain broadly in equilibrium. Put simply, '*No special efforts have therefore to be made either to bring them back or to replace them'* (Ehrenberg, 2000, p.42). But if the *cumulative* customer base continues to expand with ever more occasional buyers over long time periods not considered by earlier studies, perhaps the proportion of new or returning customers needed in each successive year *increases* because some brand buyers have propensities so close to zero that they do become "lost for good". Stable annual sales would then depend more on increasing numbers of *new* buyers in each successive year. Identifying an empirical benchmark among continuously reporting buyers over several years would create a useful management target to link cumulative penetration building outcomes to the here and now. It would partly help to address an often-voiced criticism of short-termism in marketing (e.g. Lodish & Mela, 2007), and therefore RQ4 is proposed:

RQ4. How important to brand sales in a one-year period are households who did not buy the brand at all in the previous year?

Before proceeding to the data and analysis section we elaborate further on the NBD.

The NBD

The NBD, introduced into the marketing literature by Andrew Ehrenberg over sixty years ago (Ehrenberg, 1959), is an appropriate model with which to examine questions involving brand purchases and related metrics over several years, being both highly generalised and parsimonious in use. Its applications have been extended from consumer packaged goods brand and category buying (Chatfield et al., 1966; Dawes, 2014; Ehrenberg, 1988; Ludwichowska et al., 2017; Uncles et al., 2010), to the use of gambling products (Lam & Mizerski, 2009; Mizerski et al., 2004), consumption of mobile phone services (Lee et al., 2011), healthy behaviours (Wilson et al., 2017), cultural venue and event attendance (Trinh & Lam, 2016), and industrial purchasing (McCabe & Stern, 2009; Uncles & Ehrenberg, 1990).

NBD theory assumes (Ehrenberg, 1988 p.127) that individuals have different propensities to buy a category or brand that are already established and remain stable *'for the time being'*. Thus, no further consumer learning takes place, and the purchase rate for each individual may be treated as if it were a discrete non-negative random variable, without the need to model any marketing mix effects. It is then widely demonstrated that purchase rates across a buying population are distributed with a probability density function closely described by a compound Gamma-Poisson, or negative binomial.

To describe the buying of a single stationary brand, the model is applied to observed purchasing in a fixed time period. The buying frequency, n of a given household in the first, and successive equal periods is assumed to follow a Poisson distribution with the parameter λ

$$f(n) = \frac{\exp - (\lambda)\lambda^n}{n!} \qquad (1)$$

with mean:

$$E[n] = \lambda$$

The long run mean purchase frequencies λ of individual households differ, but are assumed to be distributed gamma over the population

$$f(\lambda;k,a) = \lambda^{k-1}\frac{exp\left(-\frac{\lambda}{a}\right)}{a^k\Gamma(k)} \qquad (2)$$

where k and a are the shape and scale parameters of the distribution. Mixing (2) with (1), the probability density function of n in any equal period will be given by (3)

$$f(n) = \frac{(1+a)^{-k}\Gamma(n+k)}{n!\Gamma(k)}\left(\frac{a}{(1+a)}\right)^n \qquad (3)$$

with mean:

$$E[n] = ak \qquad (4)$$

and proportion of non-buyers:

$$f(0) = (1+a)^{-k} \qquad (5)$$

Once estimated from observed data, the theoretical output describes not just the expected distribution of brand purchase frequencies 0,1,2,3,….n across the population for a successive period, but also the proportion of buyers expected to repeat, the proportion that won't, and therefore the proportion that needs to be replaced to maintain stationarity. In CPG (consumer packaged goods) categories that distribution typically produces a good fit to observed data, and invariably takes the form of an 'inverse J'; namely a very large number of households buying infrequently, for example once or twice, far fewer buying 3 or 4 times, and a long tail of very few households buying more frequently.

An important feature of the model is that once fitted, under stable conditions it can be extended to describe the expected distribution of brand purchases in multiples of the original time period (Goodhardt & Ehrenberg, 1967), for example, to fit it for one quarter and extrapolate out to two quarters. Tests of NBD buying theory have often extended the model to novel contexts (Lam & Mizerski, 2009; Uncles & Ehrenberg, 1990) or decomposed buyer flows between two equal-length time periods (Wilkinson et al., 2016), but an obvious and important extension of repeat buying theory is to assess how closely the NBD estimates cumulative penetration, and the increase in light buying in the long-run. If successful, NBD theory provides benchmarks that link short term, annual, marketing objectives with strategic outcomes. Accordingly, the final research question posed is:

RQ5. How well do projected *NBD estimations describe the observed cumulative buyer base?*

Method

Data

To address the five research questions, we assembled a data set comprising household buying records from a five-year panel set provided by Kantar UK, covering the period 2009-2014 (approximately 12,400 households). The reporters in standard panels are a sample with replacement and cannot therefore reliably represent continuous repeat-purchase loyalty over the long term. Therefore, to avoid confounding panel attrition with brand defection, we filtered the panel to include only continuous reporters, retaining representative households from every standard demographic that had reported in at least 75% of the total four-week periods, including in the three first and three last in the full five year period. This procedure provides a rare and valuable dataset, that allows a detailed view of the actual buyer behaviour of individual households over an entire five years.

The research approach was to pinpoint consistent patterns generalizing in many differentiated sets of data. Four major CPG groupings were first identified to do this; home care, food and refreshment, personal care and alcoholic beverages. Maximum variation sampling (MSV) was then adopted to identify a sample of categories for analysis. MSV is a purposive sampling strategy that aims to capture the *"central themes or principle outcomes that cut across a great deal of [data] variation."* (Patton et al., 2008 p.2062).

On the basis of the diversity in their observed annual buying characteristics, ten categories were selected with annual household penetrations in a range between extremes of 94% and 27% and with average purchase frequencies between just twice a year to well over once a month (Table 1).

[Table 1 near here]

Table 1. Summary household buying metrics in ten CPG categories

Category	Annual penetration	Annual purchase frequency
Fabric care	94	7.0
Ice cream	90	15.6
Toothpaste	90	6.4
Instant coffee	85	9.5
Cook-in Sauce	83	13.1
Pasta sauce	74	10.1
Facial Care	57	5.3
Beer / lager	52	7.3
Razor blades	46	2.3
Olives	27	4.7
Average	**70**	**8.1**

Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Standard buying measures for the category and the top twenty brands (including private labels / store brands) were calculated in cumulative observation periods from a single year up to five years. We then classified the proportions of buyers purchasing each brand according to their purchase rate (e.g. 0,1,2,3,4… *n* purchases) in each time interval. This was done on a base of all households (in order to classify buyers who did not buy a brand at all in a particular year) and then as proportions in each brands' total customer base. Finally, the relative contributions of each buyer class to cumulative brand sales was established using the sales equation (penetration x purchase frequency) as in Uncles & Ellis (1989).

To project long-run outcomes for each brand with the NBD model, we first estimate the model parameters using the average purchase rate and penetration of the brand observed in the first year. This is known as the *mean and zero* method (Ehrenberg, 1988), where parameters *k* and *a* of the model are solved using equation (4) and equation (5).

From these estimates we projected cumulative purchase frequency distribution in five years for each brand by changing the parameter *a* to *5a* using equation (3) as this parameter reflects time period.

In studies such as this where differentiated replications are built in across many datasets the interpretation of findings does not depend on tests of best fit to a single dataset. Rather, it involves applying some prior knowledge to new observations, to examine "significant sameness" across different conditions (Uncles & Kwok, 2013). Thus, following Kennedy et al. (2014), data were assessed by averaging and tabulation, and then by evaluating the absolute percentage error for each buyer class and mean absolute percentage errors (MAPE) for the overall.

Results

Empirical Findings

In order to address the first research question, results are presented in Table 2 that demonstrate cumulative growth in category and brand penetration between one year and five years. In the left-hand columns we see that annual brand penetrations (averaged in rank order across the 10 categories) remained largely stationary from year to year. On the right-hand side, for comparison, as time intervals lengthen, the data show how far the values increased cumulatively, reflecting the continuous inflow of households buying for the first time since the start of year one.

The rates of penetration increase for category and brand are informative. The first row of the table shows that average category penetration increased by about 10% from year one to year two (the average annual category penetration in Y1 being 74% and the average cumulative penetration, Y1 plus Y2, being 81%, 7 points or 10% higher). But cumulative category penetration from Y1 to Y5 increased by only 20%, therefore the rate of growth slowed considerably. On the other hand, cumulative penetration growth for the average brand, the development of its customer base, followed a continuing upward trajectory.

[Table 2 near here]

Table 2. Annual and cumulative category and brand penetration over five years (Averages by share rank order across 10 categories).

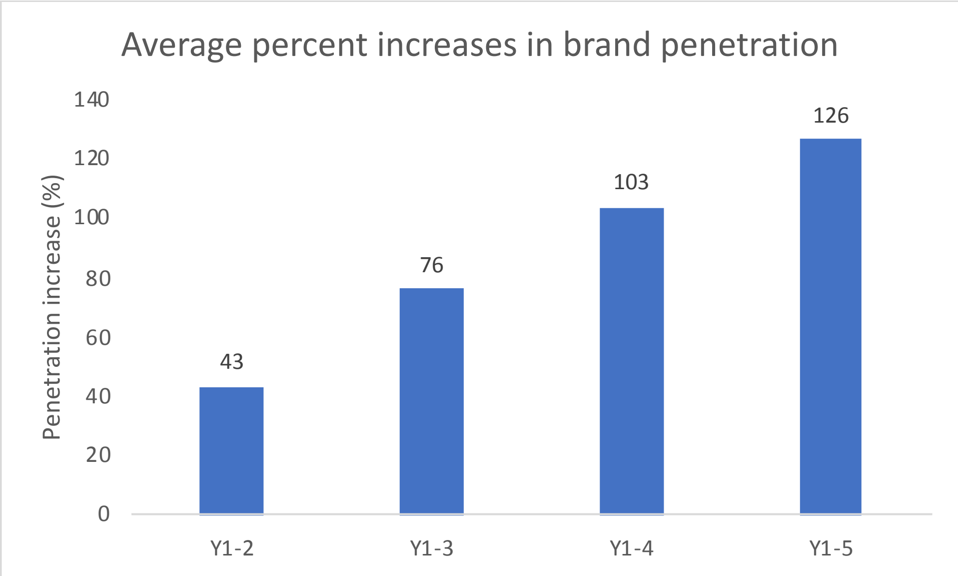
	Annual penetration (%)					Cumulative penetration (%)			
	Y1	Y2	Y3	Y4	Y5	Y1-2	Y1-3	Y1-4	Y1-5
Category	**74**	**73**	**73**	**72**	**71**	**81**	**84**	**86**	**88**
Brand 1	35	36	36	35	35	45	52	56	59
Brand 2	19	20	20	20	20	28	34	38	42
Brand 3	15	15	15	15	14	22	27	31	34
Brand 4	10	11	10	10	10	16	20	23	26
Brand 5	13	12	12	11	11	18	22	25	27
Brand 6	11	11	11	11	10	16	20	23	25
Brand 7	8	7	7	7	7	11	14	16	19
Brand 8	10	10	10	10	9	15	18	21	23
Brand 9	6	7	7	6	6	10	13	15	16
Brand 10	6	6	6	6	6	9	12	14	16
Brand 11	5	5	5	5	6	8	10	12	13
Brand 12	5	5	5	5	5	7	10	11	13
Brand 13	5	6	5	5	5	9	11	13	14
Brand 14	5	5	5	4	4	7	10	11	12
Brand 15	3	4	4	4	3	6	8	9	11
Brand 16	4	4	4	4	4	7	9	11	12
Brand 17	3	3	3	3	3	5	6	8	9
Brand 18	2	2	2	2	2	3	4	5	6
Brand 19	3	3	3	3	2	4	6	7	8
Brand 20	3	2	3	2	2	4	6	7	8
Avg stable brands (*n*=161)	**9**	**9**	**9**	**8**	**8**	**13**	**15**	**18**	**20**
Avg all brands (*n* = 200)	**9**	**9**	**9**	**9**	**8**	**12**	**16**	**18**	**21**

Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Figure 1 demonstrates that trajectory. Results for the 200 brands in the 10 categories are summarized to compare the average percentage increases from one to two years, one to three, and so on, up to five years. This reveals how, for a typical brand, cumulative penetration increases by almost half in two years, and more than doubles over five years (note at the base of Table 2 that the average annual brand penetration is 9% in Y1 but grows to 20% by Y1-Y5). The extent of this cumulative growth in the customer base has seldom, if ever, been noted before. It demonstrates how far any brand, large or small, must reach into a potential buyer base of all category users to maintain share.

[Figure 1 near here]

Figure 1. Percentage increases in cumulative brand penetration. Averages across 200 brands in 10 categories from one year to five years



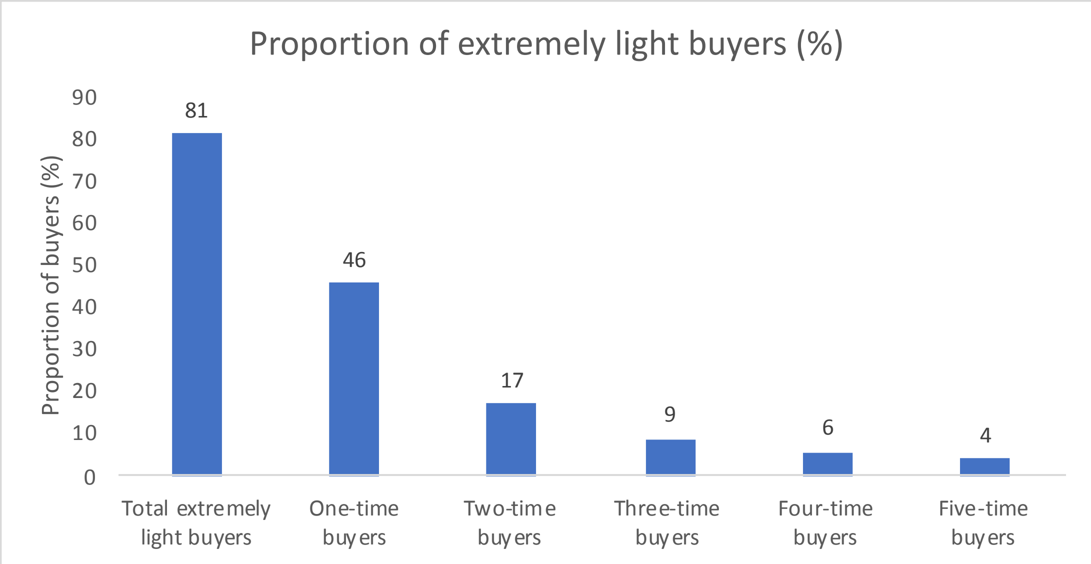
Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

The focus of the study is the cumulative growth in the customer base of stationary brands. Of the 200 brands in this sample, 161 were long-run-stable (i.e. with annual penetration changes of less than 5%), consistent with the empirical generalization of 78% reported in Dekimpe & Hanssens (1995b). At the base of Table 2 we compare the total sample values with those for the stable brands, but both show very similar results; average annual brand penetration of 9% at Y1, growing to 20% at Y1-Y5.

Answering the second research question, namely what proportion in the accumulated customer base buy at an equivalent rate of once a year or less, highlights the depth of repeat-purchase brand managers can realistically expect over the long run. Figure 2 describes the distribution of purchase heterogeneity for the lightest buyers (those buying five times or fewer) in the typical customer base.

[Figure 2 near here]

Figure 2. Distribution of light brand buyers in the five-year customer base. Averages across 200 brands in 10 categories



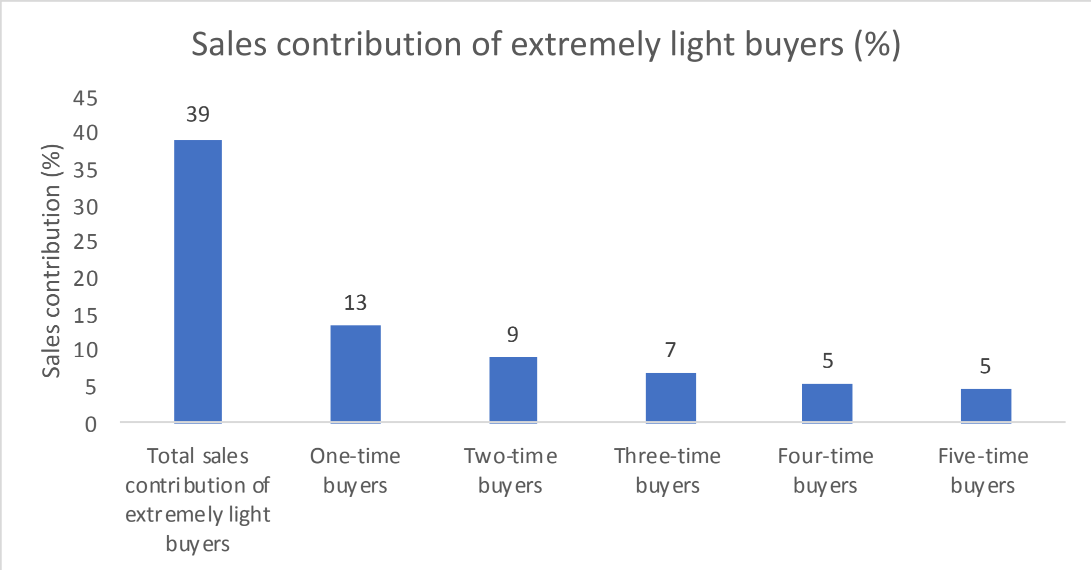
Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Values are again averaged for the top twenty brands in the ten categories. Collectively, the ‘five times or fewer’ buyers accounted for 80% of the customer base, and we find that 46% of a brand’s buyers purchased the brand just once over the five years, and 17% only twice. Consumer packaged goods are often referred to as fast moving consumer goods, but they only move fast because large numbers of individual households buy them quite infrequently (Barwise & Farley, 2004). The response to our first two research questions reveals how systematic and pronounced these characteristics of CPG brand buying become in the long run.

In response to the third research question, Figure 3 shows the relative sales contribution from the lightest buyers. Once-only buying contributes 13% of sales, two-time buyers contribute 9% and so on, and those buying a brand five times or fewer in as many years contribute nearly 40% to its total sales over that time. Given the equilibrium in the categories observed and the consistency of this result, it is obvious that attracting this part of its customer base is not optional for any brand.

[Figure 3 near here]

Figure 3. The sales contribution of extremely light buyers over the five years
Averages across 200 brands in 10 categories



Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Further, since about 80% of buyers – the lightest – make up about 40% of purchases, the result implies that in five years the *heaviest* 20% must account for approximately 60% of sales, a Pareto share of 0.60. This is greater than Sharp's (2010) annual concentration of 0.50 but substantially lower than the six-year dollar concentration of 0.73 in Kim, Singh and Winer (2017), and indeed Pareto's 0.80. Our evidence is generalized over a wide range of CPG category buying types, but there is still inconsistency on an exact benchmark. Nevertheless, two things are clear. The first is the time dependency of the metric; the second is the unexpected importance of sales to the lightest rather than the heaviest buyers.

The fourth research question pertained to the sales contribution of those customers in each year who had been *non-buyers* in the previous year. Table 3 summarizes the finding that in every year stable brands make nearly 40% of their sales to consumers who *did not purchase* in the prior year – that is, those attracted back to the brand from earlier years, or for the very first time. It highlights a relative low contribution from repeat-purchase loyalty. Ehrenberg's view in the text Repeat Buying (2000), that "no special effort" is needed to plug the continuous leak, was based on the knowledge that broadly there is really no leak –- so many buyers have low or very low propensities to purchase, that stationary brand sales result each year from a constantly changing mixture of buyers drawn from a large pool. Findings in response to the first three research questions demonstrate how large that pool is and how light its brand buying, but the evidence in Table 3 extends Ehrenberg's view - it appears that a leak hardly exists even over time. The necessary annual attraction rate of "new" and extremely light buyers is observed to be a surprisingly stable target. Consequently, whether that buying rate is any higher or lower than might be expected can be evaluated by long-run NBD projections. We describe these next.

[Table 3 near here]

Table 3: The sales contribution of last-year's non-buyers this year (%).

Category	Y2	Y3	Y4	Y5
Fabric care	30	31	30	28
Ice cream	30	31	32	29
Toothpaste	37	36	39	39
Instant coffee	26	28	23	24
Cook-in Sauce	35	36	33	32
Pasta sauce	36	36	36	33
Facial Care	47	46	45	44
Beer / lager	32	32	30	30
Razor blades	59	60	59	57
Olives	49	49	50	47
Average	**38**	**39**	**38**	**36**

Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014; 200 brands

In response to the final research question, Table 4 summarises the observed and projected values at five years for the proportions in the cumulative customer base making from one to five purchases in total. The table also shows values for the sales contribution from each class. Absolute percentage error statistics are given for each class, then summarised at the base of the table as a model mean absolute percentage error (MAPE) statistic for both buyer heterogeneity and sales contribution.

The first point to note from Table 4 is that in five years the observed light buyer class accounted for 81.2% of the total typical customer base. However, the NBD estimated those same buyer classes to account for just 67.7%, an absolute percentage error of 17% but still within acceptable bounds established for this type of fitting, (Driesener et al., 2017). Excluding one-time buyers means the predictive power of the NBD improves; the class is observed to be 50% larger than its estimate. This bias actually highlights the main finding, which is that observed repeat-purchase loyalty is systematically lighter than its NBD expectation.

[Table 4 near here]

Table 4: NBD five-year projections *vs.* observed data (%)

Extremely light buying	Proportion of total buyers			Sales contribution		
	Observed	NBD	Absolute percentage error	Observed	NBD	Absolute percentage error
One time	45.8	31.6	31	13.4	6.8	49
Two times	17.2	15.0	13	9.1	5.8	37
Three times	8.6	9.4	10	6.7	5.2	23
Four times	5.6	6.7	19	5.4	4.7	13
Five times	3.9	5.0	28	4.6	4.3	6
Total Light Buyers	81.2	67.7	17	39.2	26.8	32
MAPE %			*20*			*25*

Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Discussion and Conclusion

We now review and discuss these results and their implications for theory and management. We have demonstrated the extent to which the buying characteristics and make-up of the customer base for any CPG brand in an equilibrium market are time dependent. Competitive brand performance metrics, even in substantial management periods of as long as a year, do not easily lead to an understanding of longer-term performance outcomes. The aim of this research was to describe the evolution and predictability of buying regularities as the cumulative customer base extends in time and in size, particularly with regard to the behavioural loyalty of its lighter buyers and their relative contribution to sales. The evidence contributes five new findings to knowledge of long-term brand maintenance and growth.

First, in addressing RQ1 the study shows that the buyer bases of established categories and of the brands competing in them both grow (accumulate) substantially over five years, but in different ways. Category growth slows markedly after the first year. Brand buyer numbers increase by almost fifty percent from year one to year two and more than double from year one to year five. The rate of cumulative acquisition (i.e. bringing in new buyers in year two that did not buy in year one, and so on) needed for stability is rather faster for smaller brands than bigger, but the novel finding is the surprising extent to which, even over five years, management must continue to attract very substantial buyer numbers just to maintain brand share.

Second, in relation to RQ2, cumulative penetration growth from a notional time zero implies that the typical CPG brand is continuously attracting light buyers, many with repeat rates that are very low indeed. After five years, almost eight in ten buy the brand at a rate equivalent to once a year or less; just under half will have bought it *once only*. A question might arise, is this extremely light buying a manifestation of variety seeking (e.g. Sharma et al., 2010)? We believe it is more accurately explained as a consequence of infrequent category buying, coupled with repertoire or multi-brand buying. Take the example of a household that buys tub ice-cream only once per year. On one occasion the buyer buys brand A, the next time B. Perhaps the next time back to A. Brand A now has an interpurchase interval of two years between purchases for this household.

RQ3 pertained to the sales contribution of light buyers. The third finding from this study is that in aggregate, light buyers are more important to long-run sales performance than marketing lore suggests. Those extremely light buyers, while they do not buy often at all, account for a large proportion of brand sales over five years: 39%. The flip-side is that the long-term Pareto share is just 60:20; not 80:20. We have also calculated the average annual brand purchase frequency for the heaviest buyers (Table 5 in the Appendix) to find that typical repeat purchase rates are also surprisingly light. For example, the best customers of a toothpaste brand might buy it fewer than three times in a year and for a beer, lager or instant coffee less than once every two to three months. The finding has obvious ramifications for brand strategy, which we discuss in the following section.

Fourth, lightness of buying means that even to maintain market share, managers must keep up activity that reaches and is noticed by ‘new’ buyers. This objective is substantial: we demonstrated that in any year four in ten of a brand’s customers had not bought the brand at all in the previous year, via addressing RQ4.

Last, we found that observed long-run performance outcomes for stationary brands can still be quite closely predicted by extending the time parameter of an annual NBD model fitting. Doing so over many sets of data has identified a systematic bias which tends to *overpredict* behavioural loyalty. The main deviation is between the proportion of observed and predicted one-time buying in the customer bases of all brands, but otherwise the close approximation to long-run performance outcomes, is remarkable and managerially useful.

Implications

The results carry important implications for established marketing theory. We have extended and validated the use of the NBD as a forecasting tool for long-term brand management. Overall, the model successfully specified from annual fittings the distribution of buying frequencies at the lowest repeat rates in five years of cumulative buying. In itself, this suggests a necessary shift in research attention from an over-concentration on the management of heavy buyers, to a better understanding of the larger part of the buyer base. Its predictive accuracy in cumulative data reveals a new use for the model in developing our understanding of the relationship between short and long term buying, while accounting for the continuing stochastic nature of purchase timings. However, the model underpredicted the sales contribution of the extremely light buyers. This result is consistent with previous research on medium-term showing that the model underpredicted the sales contribution of year one non-buyers in year two (Lenk et al., 1993; Trinh et al., 2014). In explaining the under-predictions of the NBD model, both the Poisson and Gamma assumptions of the model have been questioned by previous studies (Chatfield & Goodhardt, 1973; Schmittlein & Morrison, 1983; Trinh et al., 2014). Empirical tests against the Poisson assumption show it is robust (Chatfield & Goodhardt, 1973; Dunn et al., 1983). However, empirical tests against the Gamma assumption show that this might be the reason for the under predictions of the NBD (Trinh et al., 2014). Ehrenberg (1988, p.80) also stated that some reformulation of the model is required and that the justification of NBD theory is not the theory in itself but its practical applications. Our results support this statement, the NBD theory might not fundamentally true, yet we can use the model to reasonably project long-term behaviour to help understand a brand's 'true' long-term customer base.

For managers, the implications of these results are profound. The analysis shows that in equilibrium markets, the scale of cumulative brand penetration growth is dramatic, continuous, with important consequences for typical targeting or loyalty strategies.

Figure 4 (Appendix) summarises cumulative performance data for a leading brand of laundry detergent over time by way of illustration. In each of the five years of this study the brand reached 35% of UK households and, in each year, about 5% of the population bought it five times or more – the heaviest buyers. The two flat dotted lines in the figure therefore represent a highly stable long-run brand performance maintained against competitive forces.

The category and brand penetration curves tell us however that the household composition in the 35% annual metric *must* be different in each year; the brand curve crosses the flat penetration curve at the end of year one, and by year five it has reached almost 70% of UK households. Every year brings new buyers to replace those that do not repeat. Managing the performance of year one buyers alone cannot therefore be a sufficient marketing objective.

In the figure, the thicker curve represents cumulative category growth, which is virtually saturated by year two. For the brand, this means that almost all customer acquisition beyond that point is the result of brand switching. These purchases from the buyers of other brands are expensive to acquire, but essential for market share. A typical tactic is price promotion, but split loyalties mean individual households can devote low purchase frequency to the brands they choose, returning to some after long absence. After five years the sales contribution of the lightest buyers is almost (and for the smallest brands actually is) as important as the sales to the heaviest. This means that just to maintain share, penetration growth is essential. To grow share, the brand would have to attract more buyers than it loses and reach further and faster into the headroom offered by the large pool of category buyers to do so.

Some authors have previously stressed the importance of light buyers in the annual customer base (e.g. Ehrenberg, 2000; Ehrenberg et al., 2004). The cumulative view suggests important new managerial insights.

First, the typical brand buyer is a light buyer. The majority of a buyer base buys a CPG brand once a year or even less, and so it is very easy for brands to be forgotten, especially if households buy competing brands in the meantime. This problem is exacerbated if managers make it harder for the brand to be remembered and identified. ‘Refreshing’ a brand’s distinctive assets on pack risks disconnecting consumers’ existing brand-memory structures from their on-pack cues (Romaniuk, 2018). It decreases the likelihood that the brand’s lightest buyers, for whom memories are most fragile, would recognise the brand easily or bring its associations to mind in the competitive store environment.

This risk is real. For example, Chahal (2015) cites survey evidence from senior practitioners, suggesting that over half of pack redesigns are prompted merely by organizational change (e.g. a new CMO), and a fifth confirming that they had changed brand elements based merely on a 'judgment call'. Lee, Gao and Brown document a dramatic sales drop for one orange juice brand (Lee et al., 2010) which they attribute to a packaging change that made it harder for buyers to recognise a familiar brand on-shelf.

Second, the study shows that it is important for management to think about the size of the customer base differently: in one year it may contain less than half of the households needed to maintain market share over five years. Planning strategy around the heaviest buyers in a single year is also risky. Those who buy a CPG brand in these categories at 5+ times in *every* year typically account for just 3% of the five-year customer base. It doesn't mean these households aren't important – they clearly are - but management must manage the other 97% of the total customer base or risk losing brand share.

Third, the need to maintain memory structures in the total customer base indicates a strong rationale for consistent advertising (Keller, 1999; Romaniuk & Sharp, 2004a) and mass reach media strategies over targeting (Kennedy & Hartnett, 2018). Every brand needs to target all category buyers, and why not? Category buyers do not need educating about the uses of the product, so they may need little encouragement to try a new brand that they have not previously considered. This evidence highlights the real risk of limiting penetration growth by targeting only certain parts of the market.

Finally, if brand penetration is 15% in a year it may be easy to conclude that 85% of the market don't actually like it – but the point is that non-purchase in one year is not necessarily because the brand doesn't suit some people, it is primarily because they haven't got around to buying it over the past year or two. This is the *unbearable lightness of buying* which every CPG brand must face.

Limitations and future research

The study has a number of limitations. While it has impressive breadth, covering 10 categories and 200 brands over five years of continuous buying, it is for the UK only. We call for further replications in order to develop empirical generalisations about the composition of the long-term brand buyer base, and in particular its lightest consumers. In addition, because above the line advertising remains the most important tool for reaching the lightest brand buyers, an obvious further extension is in investigating how brand advertising might be linked to the long-term evolution of the brand's buyer base.

Next, the volume of CPG sold online is still small, but has recently increased dramatically, boosted by national lockdown strategies. In the UK in 2020 it was estimated to account for 13% to 15% of all grocery (Nott, 2020). As online grows its share, it is possible that the automation or re-enforcement of brand choice from factors such as saved shopping lists or brand-name reminders may affect repertoire development over time. Anesbury et al (2016) reported very similar on and offline behaviours in terms of shopper effort using a sample of novice online shoppers. While this implies the habitual transfer of existing category and brand knowledge to the new context, other evidence remains inconsistent. For example, Hyghe et al., (2017) found a lower propensity to buy 'vice purchases' online, while Munson, Tiropanis & Lowe (2017) found from a large UK retailer that only 40% of the average basket was stable, while 60% was prompted by offers and suggestions. The three findings are not necessarily incompatible in a longitudinal cumulative view, but further research is needed.

Finally, although we found the NBD fitted these data well for annual periods, it performed less well over cumulatively longer periods. Given this, further studies might consider the non-stationarity of individual buyers and even investigate the non-repeat outcome of one-time buying. Finally, and perhaps of most interest, the data here consisted of near-stationary brands, in order to establish these norms. They can now be applied to assess the role of extremely-light buying in cases of persistent brand growth and decline, and also in total category expansion.

Acknowledgments.

[Details removed by the Editorial Office].

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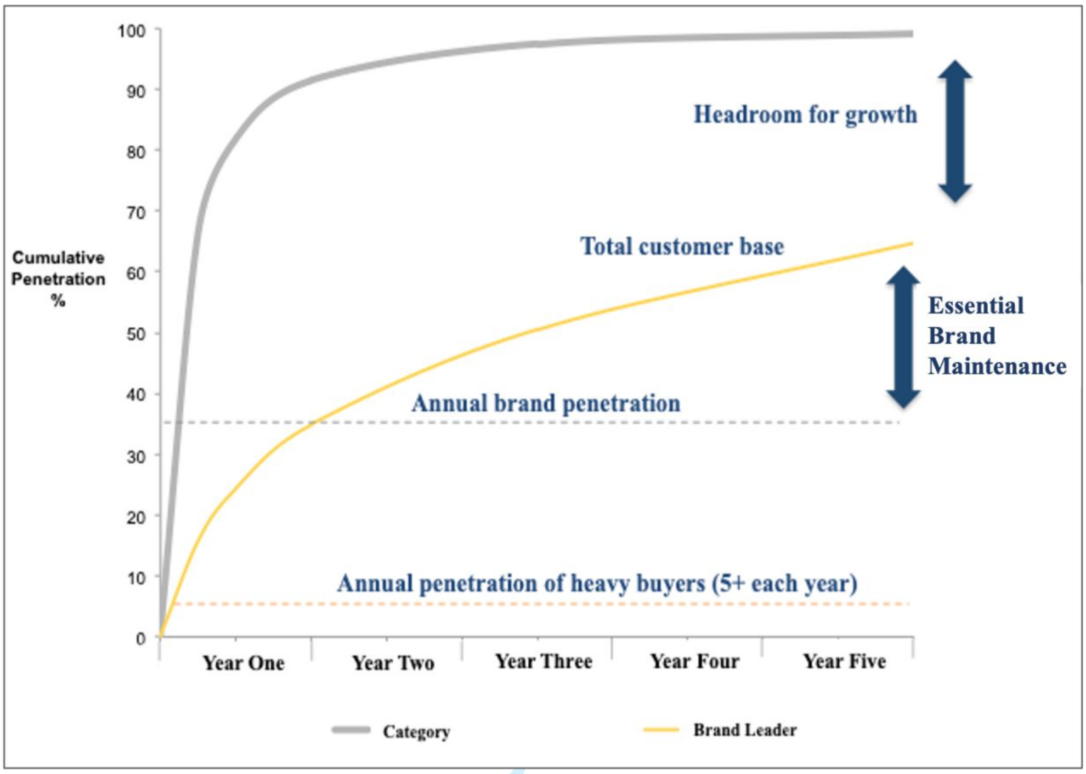
Appendix

Table 5: Average purchase frequencies of heavy brand buyers in ten categories

Category	5 Years	1 Year
Fabric care	17	3.4
Ice cream	19	3.8
Toothpaste	14	2.8
Instant coffee	22	4.3
Cook-in Sauce	23	4.6
Pasta sauce	19	3.8
Facial Care	14	2.8
Beer / lager	21	4.3
Razor blades	11	2.3
Olives	17	3.4
Average	**18**	**3.6**

Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Figure 4: Cumulative penetration growth for category and brand in fabric care



Data source: Kantar Worldpanel. 12,400 continuous UK reporters 2009 to 2014

Reviewer 1	**Authors' Response**
You have addressed all my concerns.	
Reviewer 2	
I remain very supportive of this study and I acknowledge the authors' efforts in rewriting/reshaping a significant proportion of it. Several aspects have seriously improved. The research questions offer a clear path to follow the rationale for the empirical analysis and the discussion of the results. The introduction is also broadly improved, with a clearer story being told, which is nicely signposted in the discussion, albeit primarily from the perspective of managerial implications. To reach publication standards, I suggest one more round of refinements and improvements, mainly in language and theory. My remaining comments are as follows:	Thank you for your encouragement, and for these further suggestions to improve the paper. We have detailed our responses below and noted the changes in the manuscript.
1) The abstract still retains some traces of jargon and technicality, which detract from a simpler story everyone can understand. It's also lacking a nice acknowledgement of the extent to which this study advances a longstanding tradition of research on stochastic models of consumer buying behaviour, with the NBD clearly taking the center-stage in light of the advantages for the analysis of customer bases and contribution to sales.	Thank you. We have further refined the abstract to clarify the intended meaning, and we have taken the opportunity, as you suggest, to promote our contribution to NBD theory. We felt a statement specifically highlighting the theory advancement was most appropriate in the summary statement of contribution, in which we now say: 'We advance NBD theory, demonstrating how a stochastic model can still explain and project these changes from annual fittings, to link the 'here and now' with long term brand performance'. (p.1).
2) The introduction is much better, but I recommend another bit of revision, signposting the key aims in parallel to the RQs. The theoretical contribution is a bit underplayed, but getting there. I would also mention the value of the dataset.	Thank you for these suggestions. We have now added a summary of the RQs such that they more easily follow from the principal aims of the study. We mention the slightly more explicit statement about theoretical contribution in the reply to the point above. We mention the value of the dataset in the data section, (we thought it was best placed there) saying 'This procedure provides a rare and valuable dataset, that allows a detailed view of the actual buyer behaviour of individual households over an entire five years'. (p. 20).
3) Regrettably, the literature review remains a bit of a let down for me. Some rethinking is needed in terms of the organisation and logical flow of the sections. I would start with NBD and Pareto (details/literature on Pareto and references on it come too late in the picture). I would take a chance to perhaps summarise more rigorously and from a chronological perspective extent relevant research. There are omissions and jumps. For example, you state: "Another stream of purchase research began in the 1980s relating to the distribution of inter-	Thank you for this point. It is a deliberate decision in this review not to start with the NBD, but to go "data first" with the development of knowledge and empirical generalisations about heavy and light category and brand buying. The way in which we have structured the review is that it moves from the simplest efforts ('light/heavy') to the idea of a distribution of lights to heavies, to a *model* for this phenomena. The logic then turns to the model as one established tool that has been used historically for benchmarking and predicting generalising data

purchase times for product categories" - no reference given. Watch out for the remaining traces of undefined concepts and acronyms too (e.g., SCR - I assume, Share of Category Requirements?). In general, I recommend moving the NBD section forward.	regularities across contexts, and therefore one that might be extended to this novel condition in order to build explanatory theory. The RQs then flow in an order that reflects the research approach, considering empirics first in many sets of data and then benchmarking any regularities to generalise an existing model rather than going theory first to fit a new model to a single dataset. We have now included relevant references for the statement relating to purchase intervals. We have also elaborated on acronyms such as SCR.
Please also clarify: "NBD theory assumes that..." - unclear and unreferenced.	Thank you for the suggestion, we have added a summary of relevant research on the extension of the NBD and concluded that given our study using FMCG brand data, the NBD is an appropriate model to use. Below is the addition. Another well-known generalised model of the original NBD model is the Pareto-NBD model. Schmittlein et al. (1987) argued that the Poisson distribution only accounts for active customers. “Death” or “drop out” customers are not Poisson. They follow the Pareto distribution (Johnson & Kotz, 1970). The Pareto/NBD is highly regarded for customer base analysis in the marketing literature. Recently, many researchers have extended this model in different areas (Abe, 2009; Batislam et al., 2007; Bemmaor & Glady, 2012; Fader et al., 2005; Jerath et al., 2011; Reinartz & Kumar, 2003). For example, Fader et al. (2005) developed a new model, the beta-geometric/NBD (BG/NBD), which is easier to implement than the Pareto/NBD model. Batislam et al. (2007) modified the BG/NBD model to the MBG/NBD model which allowed customers drop out at time zero (immediately after the first purchase). Abe (2009) extended the Pareto/NBD model using a hierarchical Bayesian (HB) framework to focus on customised marketing. Bemmaor and Glady (2012) proposed to replace the Pareto distribution with a gamma mixing of Gompertz distributions (G/G), which allows for the probability density function to be skewed to the right or to the left; and its mode can be at zero or shift away from zero. A non-zero mode might occur when the organisation offers strong differentiation and has a strong reputation, such as high-end hotels and up-scale catalog retailers (Bemmaor and Glady, 2012). The Pareto/NBD model is proposed for organisations that have information on initial purchases and former customers who are no longer active. Some examples are catalogue mailing lists, church directories, dentist and beauty salons’ files, department store charge card records, and triers of a new grocery product (Schmittlein et al., 1987). At the brand level, the Pareto/NBD has some potential for monitoring sales

	of a newly introduced brand, but is not recommended for established brands in markets such as FMCGs (Morrison & Schmittlein, 1988). The reason is that, for a mature brand, it is difficult to identify when a consumer made the initial purchase of the brand. For example, it is difficult for Colgate to identify when a given consumer made the initial purchase. It is also difficult to identify if a given consumer is permanently inactive unless the consumer is literally dead. A consumer might have not bought Colgate for months or years but there is still a probability that the consumer will buy Colgate again in the future. Thank you for your further comments. We have: • (Page 7) added references to the Erlang distribution of interpurchase timing, notably Jeuland, Bass, & Wright (1980). • (Page 7) expanded Share of Category Requirements for SCR. • (Page 16) Referenced "NBD theory assumes that…." (Ehrenberg, 1988 p.127) before expanding on it.
What does it mean that it is an 'appropriate' model'?	We have amended the statement in question, it now says The NBD, …….. is an appropriate model with which to examine questions involving brand purchases and related metrics over several years, being both highly generalised and parsimonious in use. The purpose of the section on the NBD is to expand on why it is an 'appropriate model', and why it is worth testing in this novel condition. We point out that it is already highly generalised but simple in its application. Having described the model and its theoretical assumptions, the section closes (p.18) by explaining that under stationarity it can be extended from an annual fitting to describe the buying in the accumulated five year customer base. If it does so successfully it extends knowledge of repeat buying to the long term – but at present these things are not tested, a current deficiency in knowledge.
4) The section on the RQs is starting to work. A bit of the rant-like writing style from the previous draft remain, whereby multiple in-text rhetorical questions are posed, before reaching the formal RQ. Also, with RQ5 you shoots yourselves in the foot in choice of model. Maybe add it as an additional aim, and move into the methods? Something along the lines of wanting to go the extra mile and to add more robustness to the conclusions you verify that as well? Also, I get your point on parameters... But they are mentioned in the equations after all. A few brief comments on the meaning and interpretation is	Thank you. We have removed two more rhetorical questions from this section (page 15). We are not sure why we have shot ourselves in the foot – in developing the final RQ we have explained the limitations in our knowledge of the NBD model and set up a new test in many sets of data to extend and replicate its application to cumulative long-run buying. We believe this deserves a separate RQ.

perhaps warranted.	
5) Theoretical implications in the discussion - I am afraid you are resting the results vs. your RQs. Good and nice to read, but NOT the same as an adequate discussion of the theoretical implications...	Thank you, we have extended the theoretical implications including discussion on the NBD model assumptions as well as using the NBD theory to understand a brand's true customer base. Below is the revision: The results carry important implications for established marketing theory. We have extended and validated the use of the NBD as a forecasting tool for long-term brand management. Overall, the model successfully specified from annual fittings the distribution of buying frequencies at the lowest repeat rates in five years of cumulative buying. In itself, this suggests a necessary shift in research attention from an over-concentration on the management of heavy buyers, to a better understanding of the larger part of the buyer base. Its predictive accuracy in cumulative data reveals a new use for the model in developing our understanding of the relationship between short and long term buying, while accounting for the continuing stochastic nature of purchase timings. However, the model underpredicted the sales contribution of the extremely light buyers. This result is consistent with previous research on medium-term showing that the model underpredicted the sales contribution of year one non-buyers in year two (Lenk et al., 1993; Trinh et al., 2014). In explaining the under predictions of the NBD model, both the Poisson and Gamma assumptions of the model have been questioned by previous studies (Chatfield & Goodhardt, 1973; Schmittlein & Morrison, 1983; Trinh et al., 2014). Empirical tests against the Poisson assumption show it is robust (Chatfield & Goodhardt, 1973; Dunn et al., 1983). However, empirical tests against the Gamma assumption show that it might be the reason for the under predictions of the NBD (Trinh et al., 2014). Ehrenberg (1988, p.80) also stated that some reformulation of the model is required and that the justification of NBD theory is not the theory in itself but its practical applications. Our results support this statement, the NBD theory might not fundamentally true, yet we can use the model to reasonably project long-term behaviour to help understand a brand's 'true' customer base.
6) Super minor: Please add data labels on each bar in the figures with histograms.	Thank you, we have added these numbers in

We thank the reviewer for their support for the work and effort put into these constructive recommendations. We hope that the paper is not suitable for publication in Journal of Marketing Management.

Authors

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