Investigating undercurrents of stationarity and growth with long-term panel data

Abstract

There have been frequent calls in the literature for a more comprehensive understanding of marketing impact on long-term firm performance (Hanssens and Pauwels, 2016; Lodish and Mela, 2007; Webster and Lusch, 2013). Retail scanner data has been the principal source of empirical evidence in this strategic domain, but it cannot explain the behavioural shifts that underpin the sales dynamics it reports. With the availability of far larger and extended household panels, it is now possible to observe the effects of accumulating penetration on brand and category buying over many years. This type of data nevertheless presents theoretical and methodological challenges to researchers. In this paper we discuss an approach to extending established marketing theory to long-run repeat buying, then outline the inherent constraints of long-term panels. We illustrate these challenges using one, five, and ten-year panel datasets and present a research agenda to progress explanatory theories of long-run brand building and category growth in this new but so far mostly untapped resource.

Investigating undercurrents of stationarity and growth with long-term panel data

1. Introduction

Marketing management remains under pressure to demonstrate long-run impact from its considerable annual budgets (Binet and Field, 2007; Binet and Field, 2013; Hanssens and Pauwels, 2016; Webster and Lusch, 2013). Nevertheless, marketers are routinely criticised for their short-sighted perspectives on brand performance and for chasing short-term sales outcomes (Lodish and Mela, 2007). Overinvesting in the short-term comes at the expense of longer-term outcomes, which accumulate from a brand's sustained activities over years and even decades. Effective long-term marketing strategies are necessary for firms to achieve sustained growth and profitability (Hess, 2016).

The data and metrics that firms commonly rely on to assess performance may contribute to this short-termism (Lodish and Mela, 2007). Retail scanner data has long been a staple empirical resource for consumer goods firms to assess brand and category sales. This data can provide marketers with near-immediate insights into the outcomes of tactics such as price promotions, which often have dramatic sales spikes (Blattberg et al., 1995; Gedenk et al., 2006). Observing this data over just one or two quarters might give the impression that price promotions are critical to brand growth. However, when marketing mix elements are assessed over multi-year periods, the effects of price promotions are far less than those from advertising, distribution, and product line investment (Ataman et al., 2010). In contrast to price promotions, it is much more difficult for marketers to identify any short-term sales outcomes from advertising campaigns in scanner data, even with the use econometric modelling (Dawes et al., 2018).

Lack of access to long-term datasets is itself a major impediment to firms adopting long-term marketing perspectives. Despite the long sales histories of many brands, firms will

typically only have a clear view of the most recent periods. Lodish and Mela (2007) report that many firms only purchase access to data reporting the past 52 weeks. Without appropriate long-term data, the measurement of marketing's long-term effects is then generally subsumed into more indirect measures, such as brand awareness, brand equity or the ability to charge a price premium (Hess, 2016).

Gaining access to retail scanner data over longer timeframes may be valuable for identifying long-run sales trends. However, it still presents a significant limitation. It cannot explain the behavioural shifts underlying those dynamics. To plan effective brand and category investment, managers need to know whether predicted long-run sales effects are achieved by increasing buyer numbers, retaining customers, raising repeat purchase rates, or some combination. Consumer purchasing records from household panel data are required to provide these behavioural insights to the sales response. While firms typically purchase household panel data to track brand performance, it still remains an under-used resource from which to establish the realistic behavioural objectives underpinning long-term growth, or even sustained performance.

Even when firms have access to panel data over consecutive years, scope for long-term insight may be limited by the purchase metrics adopted. Penetration and any related metric such as purchase frequency or repeat rate, are time-dependent but commonly reported in shorter quarterly or annual periods in time series. Slicing the data into these reporting periods provides marketers with an incomplete and potentially misleading picture of their brand's performance, the buyer base composition, and the strategies needed to achieve sustained growth.

The availability of long-term continuous panel data presents significant opportunities for firms focused on combating their marketing myopia. However, its use also raises theoretical and methodological challenges. The theoretical challenge is to establish how

marketing knowledge, developed in shorter time frames restricted by available data, continues to explain repeat-buying outcomes over a longer time frame. The need here is to extend existing knowledge so that it connects short to long term and identifies whether and when length of time may act as a boundary condition. This is critical for providing evidence-based norms and expectations of brand performance over multi-year periods. We present early findings from several long-term datasets to illustrate this challenge then discuss a promising line of attack for the future. The methodological challenges are related to the fundamental considerations and limitations in approach facing researchers who analyse household panel datasets covering many years of continuous buying. We summarise these as a set of new research opportunities that inform various dimensions of the same problem, then conclude by bringing the two challenges together in the form of a future research agenda.

2. The theoretical challenge - understanding long-run repeat-buying

Knowledge of the repeat buying of brands and categories has been developed through models such as the NBD (Ehrenberg, 1959; Goodhardt and Ehrenberg, 1967), the NBD-Dirichlet (Goodhardt et al., 1984), and the Pareto/NBD (Schmittlein et al., 1987; Fader et al., 2005). These models have become generalised in theory and widely adopted in practice. They have gained popularity due to their ability to predict and explain the complex "mechanics" of aggregate behavioural purchasing patterns across a population when individual households hold different, established, brand repertoires and buy a category at different but steady rates. Underpinning these models is an assumption of stable purchase propensities *"for the time being"*, which in practice means that the models explain outcomes well if brands and categories conform to conditions of 'near-stationarity'.

The theoretical assumptions for these models and the empirical generalisations they describe are referred to as Laws of Marketing (Sharp, 2010), and together they define how

brands grow. Robust empirical support for these models continues to be observed in household panel data aggregated at monthly, quarterly or annual levels (Ehrenberg, 1988; Ehrenberg et al., 2004). Therefore, there is ample motivation to generalise or extend the laws to the long term – to progress robust evidence-based knowledge of brand building, and to better understand growth for the whole market (category). Category dynamics tend to be gradual, and so progress has been limited by the short-term nature of most household panel data, although recent findings have identified that penetration is essential for growth here also (Dunn et al., 2019; Nenycz-Thiel et al., 2018b). As firms now start to examine their household panel data over periods between one and five years or even longer, marketing theory must advance to provide norms and guidance of what to expect.

In the following sections, we first suggest how long-term panel data can be analysed to reveal the behavioural underpinnings of brand and category performance. We then present several analyses that reveal when, and the extent to which, existing knowledge of consumer behaviour approaches boundary conditions.

2.1 Long-term brand buying – an example

Businesses typically plan in one, three, and five-year cycles (Webb, 2019). We start with an example of household panel metrics, reporting repeat buying for a single, leading, UK laundry detergent brand over 20 quarters (five years). We will be referring to this example in the theoretical challenge section to help illustrate the key points. Table 1 shows observed market share, penetration, and mean purchase-frequency outcomes from a continuously reporting sub-set of households extracted from a standard panel. Following Chatfield (1989), we take the mean value of each of the four quarterly-metrics each year to smooth the data and reduce the signal to noise ratio. The share performance of this detergent brand is seen to be at least near-stationary.

Table 1: Near-stationary quarterly brand performance over five years

Average Quarter	Brand Share (%)	Penetration (%)	Purchase Frequency (Avg.)
In Year 1	18	18	1.5
In Year 2	16	16	1.5
In Year 3	16	16	1.5
In Year 4	16	15	1.5
In Year 5	16	14	1.5
Average	**16**	**16**	**1.5**

Data Source: Kantar WorldPanel 20 Quarters, 2010 to 2014. Leading detergent brand: c.12,000 continuous panellists

In equilibrium, market share metrics (the relative proportion of total sales) will also remain constant in different aggregations – a quarter, a year, or even in five years. However, these time-bound measures fail to provide marketers with an accurate perspective of the size and behaviour of the brand's buyer base. To determine more clearly what happens as sales accumulate over a five-year period, the detergent brand share was plotted in successive quarters against cumulative penetration and purchase frequency outcomes from a notional "first" quarter in Year 1. This analysis required a panel of households filtered for continuous reporters over this period. The plot (Figure 1) shows how, over time, stationary share depends upon a dramatic increase in the size of the customer base and steady growth in repeat buying. The penetration levels attained to maintain that stationarity double from 16% to 35% by the end of the fourth quarter, and although cumulative penetration growth slows, the brand reaches *two-thirds* of the panel by the end of the fifth year. The average purchase frequency also continued to increase, from 1.5 occasions in a quarter to 2.8 in a year and so on. Figure 1 also includes theoretical penetration and frequency values for comparison, which will be discussed in the next section.

Figure 1. UK Detergent Brand. NBD predicted & observed cumulative sales equation
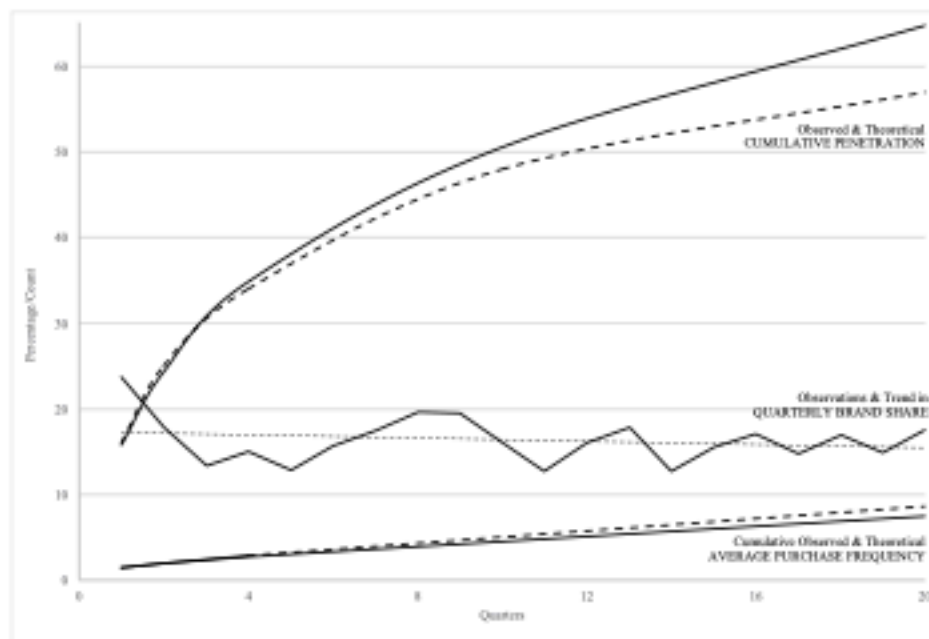
Data Source: Kantar WorldPanel 20 Quarters, 2010 to 2014. Leading detergent brand: c.12,000 continuous panellists

When household panel data is only reported in quarterly or annual periods, this crucial perspective of increasing cumulative penetration and frequency may be entirely missed. The main implications for this established and leading brand are, for example, that: (1) half of its ultimate buyers do not buy it at all in year one; (2) stationary share involves new brand buyers offsetting the sales of previous brand buyers who do not repeat purchase; (3) a substantial proportion of the "new" consumers must be extremely light buyers of the brand; and (4) the stability of quarterly or annual performance metrics (e.g. Table 1) may easily give a misleading view about the size and loyalty of the buyer base. By observing and tracking long-term metrics from continuous panels, brand managers can now more accurately grasp the scale of the tasks involved in long-run brand management and identify the inherent limitations of targeting based on recent or even 'annual' brand buying.

2.2. Understanding long-term repeat buying under stationary conditions

Assumptions of the zero-order models, identified above, are that no further consumer learning occurs and shopper brand preferences will not change. This means that individual households will continue to purchase all brands over time in line with established propensity distributions. If a market conforms to these assumptions, the outcome will be market share stationarity.

Given that the whole purpose of marketing is to break these assumptions, the stationary condition might be expected to be temporary, a reasonable assumption perhaps for a year or eighteen months. Yet, retail scanner studies have provided extensive evidence for long run near-stationarity in market share, which is the sales outcome of fixed purchase propensities (e.g., Lal and Padmanabhan, 1995; Srinivasan et al., 2000; Dekimpe and Hanssens, 1995a). While consistent with the notion of stable purchase propensities, near-stationarity alone does not provide direct evidence of fixed purchase propensities over time. Sales outcomes from retail scanner studies cannot take account of underlying repeat-buying behaviour, due to the absence of any consumer identification. Patterns of long-run stationarity have also been identified using household panel data (Trinh and Anesbury, 2015; Graham, 2009), and the new panels now make it possible to examine the extent of fixed purchase propensities directly.

To do so we make use of a valuable feature of the NBD (Ehrenberg, 1959; Goodhardt and Ehrenberg, 1967), and NBD-Dirichlet (Goodhardt et al., 1984) models; their ability to project cumulative brand and category performance measures (including inter-period repeat, drop-out, and attraction rates) across periods of any length. For example, fitting a model based on one quarter or one year of data and predicting cumulative performance over the following years. Successful NBD estimates to annual data are not new (Schmittlein et al., 1985; Morrison and Schmittlein, 1988), but the robustness of these projections over longer

timeframes has not been thoroughly investigated. Long-term continuous panel datasets now allow for such extensions to NBD theory.

To demonstrate how closely existing assumptions of repeat buying may project over more extended time, we first refer to our initial example of the leading UK Detergent Brand. This brand had a stationary market share over five years but continued to grow its cumulative penetration and purchase frequency. In Figure 1, we include NBD projections as theoretical comparators (shown as dotted curves), estimated from the brand's performance in the first year, to describe the continuing outcomes of the stationarity assumption.

The estimates demonstrate the substantial scale of cumulative penetration growth over time that is associated with the long-run stationary share. However, as the period of observation is lengthened, there are progressive deviations emerging between observed and theoretical values. Over five years, the NBD has underestimated penetration by as much as 18%, but over-estimated loyalty by a purchase or so. The bias suggests higher brand switching than anticipated; that the individual purchase propensities underlying stationary brand share performance do not remain entirely stationary over the long term. To evaluate competitive response in a way that captures this deviation, brand performance data across rivals can be modelled simultaneously using the NBD-Dirichlet.

We next present a snack foods category from the United States to examine repeat buying under conditions of long-run near-stationarity. Over five-years, this category maintained annual penetration levels within 88-89% and had average purchase frequency of 14 times a year. At the brand-level, market shares were stable with none changing by more than 1 percentage point from the first to fifth year.

From a continuous long-term panel, we explore the consumer behaviour underlying the observed near-stationarity, using NBD-Dirichlet benchmarks. Using category and brand performance metrics from the first year (2012) cumulative theoretical benchmarks were

projected for each of the following years. A special feature of the NBD-Dirichlet model is that it predicts performance metrics simultaneously for all nominated competing brands from just a handful of inputs. The observed (O) cumulative brand penetration and purchase frequencies after the first and fifth years are presented in Table 2, alongside their theoretical (T) values.

Table 2: US Snack Food Category NBD-Dirichlet Fits – 1 & 5 Years

	Penetration (%)						Purchase Frequency					
	1 Year (2012)		5 Years (2012-2016)		Deviations (O/T)/T %		1 Year (2012)		5 Years (2012-2016)		Deviations (O/T)/T %	
	O	T	O	T	1Y	5Y	O	T	O	T	1Y	5Y
Brand A	57	61	84	80	*-6*	*4*	5.9	5.6	20.4	21.1	*6*	*-3*
Brand B	30	30	57	46	*0*	*24*	3.9	3.9	9.7	12.7	*0*	*-23*
Brand C	26	21	50	33	*24*	*51*	2.9	3.6	6.9	11.3	*-19*	*-39*
Brand D	25	21	55	33	*20*	*67*	3.0	3.6	7.8	11.3	*-16*	*-31*
Brand E	10	15	20	24	*-33*	*-17*	5.0	3.4	13.1	10.6	*46*	*24*
Private Label A	9	14	18	23	*-35*	*-20*	5.3	3.4	13.7	10.5	*56*	*31*
Brand F	11	12	28	19	*-6*	*47*	3.4	3.4	6.7	10.2	*1*	*-35*
Private Label B	10	11	23	19	*-12*	*24*	3.6	3.3	7.5	10.2	*8*	*-27*
Brand G	12	9	26	16	*27*	*67*	2.7	3.3	5.1	10.0	*-18*	*-49*
Brand H	8	8	18	13	*4*	*41*	3.1	3.3	6.1	9.8	*-5*	*-38*
Brand I	8	8	23	12	*6*	*84*	3.1	3.3	6.1	9.8	*-5*	*-38*
Brand J	6	6	17	10	*2*	*73*	3.0	3.2	6.3	9.7	*-7*	*-35*
Brand K	5	4	15	7	*16*	*108*	2.5	3.2	4.2	9.5	*-22*	*-56*
Private Label C	4	4	9	7	*-2*	*31*	3.6	3.2	10.3	9.5	*13*	*8*
Brand L	5	4	13	7	*25*	*94*	2.6	3.2	3.7	9.5	*-18*	*-61*
All Other Brands	56	56	83	76	*0*	*9*	5.2	5.2	16.4	19.0	*0*	*-14*
Average	**18**	**18**	**34**	**27**	**2**	**43**	**3.7**	**3.6**	**9.0**	**11.6**	**1**	**-24**

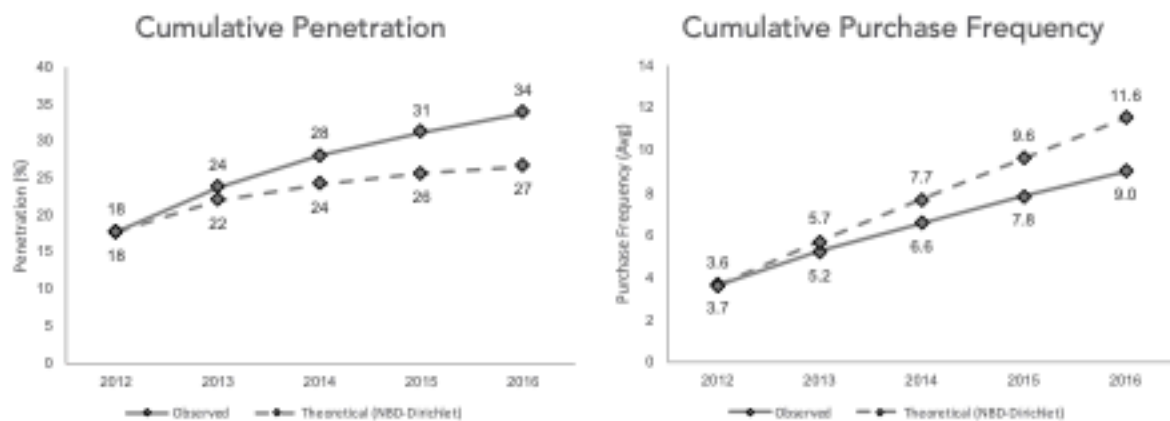*Data Source: Kilts Nielsen Consumer Panel Dataset, 2010 to 2014. 33,572 continuous panellists.*
O=Observed, T=Theorical (NBD-Dirichlet)

The NBD-Dirichlet predictions for the first year provide a good fit for the category. The average observed and theoretical values across brands closely match for penetration (both 18%) as well as purchase frequency (3.7 and 3.6). There are some deviations at the brand-level, such as Brands C and D having excess penetration (i.e., 'Change of Pace') and Brand E and Private Label A having excess loyalty (i.e., 'Niche'). These types of brand-level

deviations are common in Dirichlet markets and have been previously documented with quarterly and annual data (Scriven et al., 2017).

The novel approach here is in exploring how well the five-year NBD-Dirichlet projections fit empirical cumulative performance, given near stationarity from year to year. This model also under predicts cumulative penetration (avg. 27% v 34%) and over predicts rates of purchase frequency (avg. 11.6 v 9.0). Figure 2 shows how these deviations accumulate over the full five years in a similar manner to the UK Detergent example.

Figure 2. Avg. cumulative performance across US Snack Food brands (Observed and NBD-Dirichlet predicted).

Data Source: Kilts Nielsen Consumer Panel Dataset, 2010 to 2014. 33,572 continuous panellists.
O=Observed, T=Theorical (NBD-Dirichlet)

There is a consistent pattern of deviations between observed and theoretical penetration measures, becoming more positive from the first to final year, across all brands in the category. The inverse occurs with purchase frequency deviations, which become more negative. A notable outlier in the Snack Food category is the market leader, Brand A, which shows a much closer fit with its theoretical predictions than all other brands.

It is clear from the UK Detergent brand and US Snack Food category that long-run brand performance can remain stationary without individual purchase propensities being fixed. Yet, more work is needed to document long-run repeat buying across different

conditions (e.g., countries, categories, brands, consumers) and the relationship with the well documented phenomena of long-run market share stationarity in retail scan sales (Lal and Padmanabhan, 1995; Dekimpe and Hanssens, 1995a; Srinivasan et al., 2000). This research is critical for providing evidence-based benchmarks for long-term brand performance, knowledge necessary before any attempts to refine the NBD/NBD-Dirichlet models is undertaken to improve multi-year predictions.

These examples reflect findings from a recent study by Dawes et al. (2020), which used a long-term continuous panel to examine the erosion of annual repeat purchase loyalty for stable brands over five successive years. Continuous losses in repeat buying rates were consistently balanced by gains in attracting new buyers, resulting in no reduction in overall share. This indicates that purchase propensities are not fixed, but change over time, and that these changes are related to category and brand characteristics, as well as marketing mix factors such as range and promotions. Dawes et al. (2020) is another example of how continuous panel datasets can extend marketing knowledge to the long-term. Erosion of repeat buying had been previously documented (East and Hammond, 1996; Ehrenberg, 2000), but only at quarterly aggregations and never for more than 18 months.

Consumers' purchase propensities may also start to alter over extended periods as they go through different life stages, which may disrupt their long run buying behaviour. For example, changes in category and brand purchasing may occur as consumers enter adulthood, get married, start families, experience income changes, move to a new city or retire. Trinh et al. (2014) identify a U shape loyalty response curve with younger and older households being rather more loyal, but similar changes in loyalty have not been tracked for the same households over time. When panel samples only contain continuous reporters, covariates in life-stage variables could also be explored.

2.3 Assessing time as a boundary to Dirichlet theory

New types of panel data open the door to further research, testing the laws of marketing and their related theory over longer time frames. Rather than attempting to create new theory, it is more sensible to discover extensions that will intuitively link long-term outcomes to short term decision making, with powerful implications for those researching or managing long-run brand performance.

Empirical support for the NBD-Dirichlet support has come from extensive replication across different product types, countries, consumers, years, and market conditions (Ehrenberg et al., 2004). This has involved household panel data being aggregated across lengths of time (e.g., month, quarter, annual) (Ehrenberg, 1988; Ehrenberg et al., 2004), but rarely with purchasing data covering more than 12 months. Longer datasets of continuously reporting panellists enable time to be investigated as a possible boundary condition for the NBD-Dirichlet model and its underlying assumptions.

We use the Aluminium Foil category as an example category to examine NBD-Dirichlet model predictions at different levels of time aggregation. To assess the various fits of the model, we use a series of goodness-of-fit statistics proposed by Driesener et al. (2017). Deviations between the theoretical (T) and observed (O) brand values are assessed in four ways for both penetration and purchase frequency: Pearson's correlation between across brands (correl), relative error between the average values (AVE), relative average absolute error (RAAE), and mean absolute percentage error (MAPE).

In Table 3, we report these goodness-of-fit statistics for the NBD-Dirichlet model applied to annual aggregations of Aluminium Foil panel data from 2007 to 2016. All of the statistics are within the empirical benchmarks suggested by Driesener et al. (2017), implying a good fit within each of the full ten years. There is some minor variation between years, but it does not follow any discernible trend over time.

Table 3: Annual Aluminium Foil NBD-Dirichlet goodness-of-fit statistics

Year	Penetration				Purchase Frequency			
	Correl	AVE (%)	RAAE (%)	MAPE (%)	Correl	AVE (%)	RAAE (%)	MAPE (%)
2007	1.0	0.8	3.9	10	0.7	1.8	10	11
2008	1.0	0.1	3.6	12	0.7	3.3	12	13
2009	1.0	0.2	2.0	11	0.9	7.8	11	14
2010	1.0	0.2	1.8	9	0.8	4.2	8	9
2011	1.0	0.2	1.9	9	0.8	3.1	9	9
2012	1.0	0.0	3.1	12	0.7	5.1	12	14
2013	1.0	0.1	2.1	12	0.7	5.6	12	14
2014	1.0	0.4	2.5	8	0.8	4.3	8	9
2015	1.0	0.1	1.4	7	0.8	4.7	7	8
2016	1.0	0.1	1.4	7	0.7	2.1	7	7
Average	**1.0**	**0.2**	**2.4**	**10**	**0.8**	**4.2**	**10**	**11**

Data Source: Kilts Nielsen Consumer Panel Dataset, 2007 to 2016. 17,054 continuous panellists.
Fitting statistics (Driesener et al. .2017) for Penetration: Correlation: ≥0.9. AVE (%): ≤5%. RAAE: ≤15%. MAPE: ≤20%
Fitting statistics for Average Purchase Frequency: Correlation: ≥0.6. AVE (%): ≤10%. RAAE: ≤20%. MAPE: ≤20%

Fitting the NBD-Dirichlet model to annual data, as in Table 3, is a common procedure. The new approach that we report in Table 4 is fitting the model to longer-term data aggregated for periods of five and ten years. Despite the model fitting well within consecutive annual periods, it does not mean the model assumptions will necessarily hold when assessing the repeat buying behaviour over periods up to a decade long.

The two leaders, Brand A and Private Label, show a similarly close fit even when the time is expanded to five years; and the fit is astonishingly maintained over ten years. However, greater deviations between observed and theoretical values begin to emerge for smaller brands as the analysis window is expanded. For Brand B over ten years, the model has under-predicted penetration by 5pp and over-predicted frequency by 1.5 occasions. These deviations arise as Brand B declined from a 5% share brand in 2007 to less than 1% in 2016. This decline for Brand B is accumulated over the decade, despite the brand can still appear to be conforming to near stationarity in any one year.

Table 4: Long-term Aluminium Foil NBD-Benchmarks

	1 Year (2007)				5 Years (2007-2011)				10 Years (2007-2016)			
	Penetration		Purch Freq		Penetration		Purch Freq		Penetration		Purch Freq	
	O	T	O	T	O	T	O	T	O	T	O	T
Brand A	37	37	1.9	1.9	72	73	5.1	5.0	81	82	7.9	7.7
Private Label	25	26	1.8	1.8	60	62	4.3	4.2	72	75	6.7	6.5
Brand B	10	10	1.7	1.6	11	8	1.8	2.6	12	7	1.8	3.3
Brand C	3	4	1.8	1.5	8	10	3.3	2.6	12	15	4.3	3.5
Brand D	3	3	1.3	1.5	11	8	2.0	2.6	14	10	2.3	3.3
All Other	2	1	1.2	1.5	7	4	1.6	2.6	21	14	2.3	3.4
Average	**13**	**14**	**1.6**	**1.6**	**28**	**28**	**3.0**	**3.3**	**35**	**34**	**4.2**	**4.6**
Correl	1.0		0.7		1.0		0.9		1.0		1.0	
AVE (%)	0.8		1.8		2.5		8.9		4.8		9.9	
RAAE (%)	3.9		10		8		18		11		19	
MAPE (%)	10		11		20		19		23		33	

Data Source: Kilts Nielsen Consumer Panel Dataset, 2007 to 2016. 17,054 continuous panellists.

To further demonstrate the length of time condition, we extended the analysis to four additional categories, Chewing Gum; Margarine and Spreads; Toilet Tissue; and Frozen Bagels. Column averages in Table 5 then indicate an increase in error as the time aggregates, although the fittings identify that the extent to which the errors increase is not consistent. Chewing Gum even presents an example where the model fits just as well over ten years as it does over just one. Time alone may therefore be unlikely to present a consistent boundary condition to repeat-buying effects on market structure.

Table 5: Long-term NBD-Dirichlet goodness-of-fit (1, 5 and 10 years)

		Penetration				Purchase Frequency			
		Correl	AVE (%)	RAAE (%)	MAPE (%)	Correl	AVE (%)	RAAE (%)	MAPE (%)
Aluminium Foil	1 Year (2007)	1.00	0.7	4	10	0.72	1.8	10	11
	5 Years (2007-2011)	1.00	2.5	8	20	0.92	8.9	18	27
	10 Years (2007-2016)	0.99	4.8	11	23	0.95	9.9	19	33
Chewing Gum	1 Year (2007)	0.99	2.7	15	15	0.93	4.9	16	18
	5 Years (2007-2011)	0.96	1.0	15	14	0.96	1.7	15	17
	10 Years (2007-2016)	0.97	2.0	14	15	0.98	4.1	15	17
Margarine and Spreads	1 Year (2007)	0.98	0.7	8	11	0.07	3.6	10	10
	5 Years (2007-2011)	0.96	0.0	10	14	0.56	2.3	13	13
	10 Years (2007-2016)	0.95	0.5	13	15	0.77	0.8	14	15
Toilet Tissue	1 Year (2007)	0.99	0.6	10	14	0.78	3.4	14	17
	5 Years (2007-2011)	1.00	1.2	20	24	0.99	6.1	25	33
	10 Years (2007-2016)	0.95	3.6	17	21	0.96	4.9	19	28
Frozen Bagels	1 Year (2007)	1.00	1.7	3	5	0.70	1.8	5	5
	5 Years (2007-2011)	0.99	0.1	10	19	0.36	2.6	18	21
	10 Years (2007-2016)	0.99	0.1	12	23	0.37	1.4	21	28
Average	**1 Year (2007)**	**0.99**	**1.3**	**8**	**11**	**0.64**	**3.1**	**11**	**12**
	5 Years (2007-2011)	**0.98**	**1.0**	**13**	**18**	**0.76**	**4.3**	**18**	**22**
	10 Years (2007-2016)	**0.97**	**2.2**	**13**	**19**	**0.81**	**6.7**	**18**	**24**

Data Source: Kilts Nielsen Consumer Panel Dataset, 2007 to 2016. 17,054 continuous panellists.

2.4 Understanding long-term repeat buying under conditions of brand growth and decline

While long-run stationarity may be the norm for most brands, other brands will still experience changes in market share. Further insights into brand growth and decline are important for marketers as they aim to navigate the conditions. Longitudinal analysis of household panel scanner data has identified that changes in market share are typically associated with greater changes in penetration than in measures of behavioural loyalty (Baldinger et al., 2002; Romaniuk et al., 2014; Nenycz-Thiel et al., 2018a; Anschuetz, 2002). However, although these studies have only looked at changes from year to year, they do reveal the longer-term repeat buying that leads to penetration gains. A brand could increase the net number of buyers year on year if they were to either (a) reduce the erosion of brand buyers, (b) attract more new/light buyers to the brand, or (c) some combination of the two.

Before examining cases of growing and declining brands, we first present examples of two stable brands alongside their rates of repeat buying erosion and attraction as shown in Table 6. Over a five-year period, both brands maintain near-stationarity, with penetration maintained at 36% for Brand A and 27% for Brand B. Consistent with the findings of Dawes et al. (2020), we observe an undercurrent of erosion in repeat buying rates from the first year. Taking the example of Brand A, 70% of the buyers from the Year 1 buy the brand again in Year 2. If buying propensities were fixed, we would expect this metric to be maintained at 70% in the subsequent years. Instead, we see it erode year on year to 62% in the fifth year. This loss in repeat brand buyers is made up through additional new and light-brand buyers. Of the households that did not purchase in Year 1, 19% bought in Year 2 and this increases to 22% by Year 5. The same pattern of attraction counterbalancing erosion is observed with Brand B.

The same analysis is conducted for the long-term buying of two declining brands. Over the five years, Brand C declines in penetration from 25% to 22% and Brand D from 26% to 22%. Both brands show erosion in repeat buying from Year 1, but this is to be expected, as seen even with stable brands. The notable difference between the declining and stable brands in Table 6 is in the rates of attraction from non-brand buyers in Year 1. From Years 2 to 5, attraction of Year 1 non-brand buyers is quite flat at 11% for Brand C and 15% for Brand D.

We also include examples of two growing brands in Table 6. From years 1 to 5, Brand E has a 5pp increase in penetration and Brand F has a 4pp increase. As with the stable brands, the growing brands show increasing rates of attraction from the cohort of Year 1 non-brand buyers. What is most surprising about the growing brands is that there is almost no erosion in repeat buying among the Year 1 brand buyers. The growth of these two brands has

come from increasingly attracting more buyers to the brand and reducing the erosion from the

existing buyer base.

Table 6: Brand buying erosion and attraction over five years (Stable, Growing, and Declining Brands)

	Penetration (%)					Purchase Occasions (Avg)				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Stable Brands										
Brand A (Snack Food)										
Brand Buyer (Year 1)	100	70	65	63	62	3.7	4.6	4.6	4.5	4.6
Non-Brand Buyer (Year 1)	-	19	20	20	22	-	2.1	2.6	2.7	2.8
All Buyers	**36**	**37**	**36**	**36**	**36**	**3.7**	**3.8**	**3.9**	**3.8**	**3.9**
Brand B (Confectionery)										
Brand Buyer (Year 1)	100	55	51	48	47	2.4	3.1	3.1	3.2	3.2
Non-Brand Buyer (Year 1)	-	18	19	20	20	-	1.6	1.9	2.0	2.2
All Buyers	**27**	**28**	**27**	**27**	**27**	**2.4**	**2.4**	**2.5**	**2.6**	**2.6**
Declining Brands										
Brand C (Coffee)										
Brand Buyer (Year 1)	100	70	62	57	55	3.6	4.6	4.4	4.5	4.5
Non-Brand Buyer (Year 1)	-	10	11	11	11	-	1.8	2.0	2.2	2.3
All Buyers	**25**	**25**	**24**	**23**	**22**	**3.6**	**3.7**	**3.6**	**3.7**	**3.7**
Brand D (Confectionery)										
Brand Buyer (Year 1)	100	56	53	48	43	2.6	3.4	3.5	3.1	3.1
Non-Brand Buyer (Year 1)	-	15	16	15	15	-	1.7	2.0	2.0	2.2
All Buyers	**26**	**26**	**26**	**23**	**22**	**2.6**	**2.7**	**2.8**	**2.6**	**2.6**
Growing Brands										
Brand E (Cookies)										
Brand Buyer (Year 1)	100	62	62	64	61	2.8	3.5	3.7	3.6	3.8
Non-Brand Buyer (Year 1)	-	20	25	30	29	-	1.9	2.3	2.3	2.7
All Buyers	**35**	**35**	**38**	**41**	**40**	**2.8**	**2.9**	**3.1**	**3.0**	**3.2**
Brand F (Condiment)										
Brand Buyer (Year 1)	100	53	54	51	52	2.0	2.4	2.4	2.3	2.3
Non-Brand Buyer (Year 1)	-	12	15	15	17	-	1.6	1.7	1.7	1.7
All Buyers	**20**	**21**	**23**	**23**	**24**	**2.0**	**2.0**	**2.0**	**2.0**	**2.0**

Data Source: Kilts Nielsen Consumer Panel Dataset, Continuous Panel (2012-2016): 33,572 panellists

We present these examples of brand growth and decline for illustrative purposes.

Extensive replication is needed to understand whether, and how, these patterns generalise

across category and brand conditions. Long-term repeat buying measures, such as erosion and attraction, also provide marketers with new metrics to view the health of their brands. Having a clearer perspective on whether a brand has an issue with retaining or attracting buyers will better diagnose the situation and inform more effective marketing responses.

Multi-year repeat brand buying metrics also provide a new lens for building theory around marketing mix effects and how to invest for long-term brand growth. If our observations of growing brands generalise further, it means that marketers aiming for growth should balance marketing interventions that reduce repeat buying erosion and recruit new buyers over the long-term. Those marketers attempting to avoid decline need to invest in tactics that will draw sales from beyond existing buyer base. However, to date, long-term marketing effects has been an area predominately investigated through analysis of retail scan sales data (e.g. Bronnenberg et al., 2000; Dekimpe and Hanssens, 1995b; Lal and Padmanabhan, 1995; Nijs et al., 2001; Ataman et al., 2010; Steenkamp et al., 2005; Van Heerde et al., 2013), without disentangling their effects on the underlying rates of repeat brand buying.

Dawes et al. (2020) found that higher levels of price promotions were associated with lower rates of repeat buying erosion. This is consistent with observations that price promotions are predominantly bought by existing brand buyers (Dawes, 2018; Ehrenberg et al., 1994), but also brings into question the ability of promotions to attract new/light buyers to the brand. In contrast, advertising may be needed for continually drawing in more buyers, given that it has been found to have a greater sales impact on light and non-brand buyers (Assael et al., 2021). The availability of continuous panels opens the door to new research exploring how advertising, price promotions and other marketing tools (e.g., distribution, portfolio, regular price) to retain and attract buyers over the long-term.

2.5 Category level dynamics

The NBD-Dirichlet assumption of stationarity at the product category level means a constant category penetration and average purchase frequency in successive periods. This is consistent with time series results from scanner data (Bass and Pilon, 1980; Nijs et al., 2001; Pauwels et al., 2002) but if, as Table 5 suggests, certain categories violate Dirichlet assumptions more than others over more extended periods, one explanation may be changes in external category conditions. Ehrenberg et al. (2004) consequently called for further Dirichlet analysis of long-term category-level trends (p.1315), and this is now possible through panel data.

We now, therefore, provide an initial, large-scale assessment of long-run category buying, analysing a random selection of 50 categories (pre-defined by Nielsen in their consumer panel dataset as "modules") to report the incidence and scale of penetration and average purchase frequency changes over consecutive years from 2007 to 2016 (Table 7).

Table 7: Change in annual penetration and average purchase frequency (*n*=50 categories)

Changes from 2007 to:	Penetration			Average Purchase Frequency		
	Absolute % Change *(Average)*	+/-5% Change *(% of categories)*	+/-10% Change *(% of categories)*	Absolute % Change *(Average)*	+/-5% Change *(% of categories)*	+/-10% Change *(% of categories)*
2008 (1 year)	4	28	6	2	12	0
2009 (2 years)	7	54	14	3	24	6
2010 (3 years)	11	70	46	4	32	12
2011 (4 years)	12	70	46	5	32	12
2012 (5 years)	15	76	56	7	48	14
2013 (6 years)	20	80	68	7	46	20
2014 (7 years)	22	84	72	7	50	22
2015 (8 years)	27	90	74	8	62	30
2016 (9 years)	29	88	80	9	70	34
Average	**16**	**71**	**51**	**6**	**42**	**17**

Data Source: Kilts Nielsen Consumer Panel Dataset, 2007 to 2016. c.62,000 panellists per year

First, looking at changes from 2007 to 2008, the buying remained relatively stable on both metrics. Average absolute changes in penetration and average purchase frequency (i.e., positive or negative changes) were just 4% and 2%, respectively. Only 6% of the categories showed penetration changes of more than 10%, and none changed purchase frequency by more than this. Therefore, the assumption of near stationary category buying is reasonably sound over a one to two-year period, at least for most of the categories sampled.

However, as the period extends, the rate of change quickly accelerates. After three years (beyond the typical view of repeat-buying in panel data), the average change from initial penetration levels was 11%, and nearly half of the categories had grown or declined in penetration by more than 10%. Extending to nine years, the average change in annual penetration from 2007 levels was 29%, and 80% of the categories had changed by more than 10%. Purchase frequency followed a similar pattern with larger change over further years, but not to the same degree as observed with penetration.

Where Ehrenberg et al. (2004) identified isolated examples of long-run category trends, we now find that after nearly a decade the majority of product categories in our sample do not remain stationary, violating one of the NBD-Dirichlet assumptions. The main change is in penetration. Again, however, 'instability' was not universal. For instance, Wet Dog Food started with 21% penetration in 2007 and also finished at 21% in 2016, never moving above 22% nor below 19%. In contrast, Whipping Cream, which also started at 21% penetration in 2007, continued to increase year on year, eventually reaching 32% by 2016.

The analysis shows that substantial trends in category buying behaviour may not be immediately apparent when observed over just a year or two, may be more common than previously thought, but play out quite commonly over the longer-term. The finding prompts a range of immediate questions, for example, are annual changes persistent? To what extent

could a single brand grow a category? Moreover, are there consistent, generalisable patterns in how categories grow and decline?

2.6 Summary – Theoretical challenges

The new panel data presents researchers with a theoretical challenge, to progress understanding of long-run repeat-buying from empirical evidence rather than from assumptions – even when they base these assumptions on sound knowledge that may be applicable for shorter than longer time periods. Developing this new knowledge becomes essential, as more firms seek to gain a longer-term brand-building perspective from their household panel data.

The results from long-term panel analysis in this paper demonstrate that long-run stationarity can occur while violating the assumption of fixed buying propensities. These changes in individual-level repeat buying provide a new perspective for understanding brand growth and decline, and the behavioural effects of different marketing interventions. As the window of observation widens (e.g., periods of five to ten years), we also see that the NBD-Dirichlet model can be less able to accurately describe the cumulative category and brand buying behaviours. It is over these longer periods that substantial growth and decline of categories become more apparent.

3. The methodological challenge - analysing panel-data over the long-term.

The broad scope of long-term panel data introduces new methodological challenges. When using household panel data over multi-year periods, careful consideration must first be given to the sample elements. Across the quarters or years, the panel composition is likely to evolve as households drop out and new households are recruited. A critical methodological consideration is whether to analyse the purchasing behaviour from the full database of all

households in each year/quarter (full panel) or from a sub-set of continuous households over the analysis period (continuous panel).

Both approaches have their uses and limitations – and these limitations need to be taken into consideration. If limitations are not addressed when developing a research approach, panel compositions can lead to misleading conclusions. In this section, we explain methodological considerations and provide empirical illustrations.

3.1. Full household panels

Household panels are quota sampled to be representative of the buying population. Efforts are made around replacement and attrition to provide demographically and geographically comparable panellists between periods. Hence, using the full panel of households in each year is suitable for analysing long-run changes in aggregate-level behavioural metrics.

Full panels are the format in which firms typically view their brand performance metrics, such as quarterly or annual rates of brand penetration and frequency. Due to the sampling procedures, any observed changes in performance are interpreted to reflect actual trends occurring in the wider market. In academic research, the full panel approach has commonly been used to investigate dynamics in brand loyalty patterns over time (Johnson, 1984; Dawes et al., 2015; Casteran et al., 2019). In this paper, we have used full panels to explore category-level penetrations and purchase frequency changes (Table 7).

3.2 Continuous household panels

While full panels can provide valuable behavioural insights, their major limitation is the inability to assess long-run buying behaviour *of the same households*. Investigating aspects of brand and category repeat buying behaviour at the individual household level

requires the data to be filtered for continuous reporting panel households. A few studies have used continuous panels when investigating long-run brand performance (Graham, 2009), consumer loyalty (Stern and Hammond, 2004; Dawes et al., 2020), repertoire size (Banelis et al., 2013) and long-term effects of marketing interventions (Mela et al., 1998b; Mela et al., 1998a; Jedidi et al., 1999). In this paper, we have used continuous panellists to examine cumulative brand performance metrics (e.g., Tables 2 and 4) and long-term rates of loyalty erosion and attraction (e.g., Table 6). Continuous panels are not commonly used in industry, but we recommend greater adoption to provide firms with a greater understanding and measurement of long-term performance and investments.

An issue with using continuous panels has historically been the sample size reduction that occurs in the filtering process. Smaller panel samples can risk sample error even for medium-sized brands and infrequently bought categories. However, panels now often contain tens of thousands of panellists; the US Nielsen Homescan Consumer Panel used in this paper, for example, has approximately 62,000 households reporting each year. Even when the panel was filtered for continuous households over ten years (2007-2016), it still contained more than 17,000 households.

3.3 Considerations when filtering for continuous reporters

One key advantage of using full panels is that key characteristics of the households are matched annually to the greater population. However, when the panel is filtered for continuously reporting households, the selection introduces distortion into the sample. For example, any demographics with higher rates of churn in panel participation (e.g., particular life stages or household sizes) will cause an under-representation in the continuous panel sample. If the filtering process results in a substantially different buyer composition in the continuous panel relative to the balanced full panel, it poses potential issues for extrapolating

continuous panel results to the broader market. This may be of greater concern to firms for reporting brand performance than for academic researchers interested in long-run buying behaviour.

A natural progression that may be overlooked is that the continuous panel will age throughout the period of analysis. With a ten-year continuous panel, the panellists will be ten years older in the final year compared to the first. The aging of the panel makes it difficult to disentangle long-term market trends from outcomes due to changing life stages. For instance, demand for categories and brands may vary as panellists move into adulthood, get married, start a family, or entire retirement. Rates of brand loyalty have also been found to follow a U-shaped relationship, with higher loyalty observed for younger and older household (Trinh et al., 2014). Similarly, household composition can change over these longer time frames. An increased rates of purchase from a household may reasonably be explained by an increase in household members (e.g., a new partner, birth of children). Such changes are balanced with the full panel but are unavoidable with a continuous panel.

If firms are to use fixed continuous samples to report long-term metrics for their brands and categories, these may even underestimate the actual cumulative penetration increases occurring in market. Younger consumers will enter the market at different points in time as they transition to adulthood, while older consumers will likely leave the market due to mortality. If households need to be present in all years of analysis, this will likely lead to an under-representation of older consumers in the earlier years and younger consumers in later years. As an example, consider a fixed 10-year panel. By the final year of the panel, it is unlikely to have panellists aged in their twenties, due to their ineligibility to join a panel a decade earlier.

*3.4 Methods for assessing continuous panels*

The issues with fixed continuous panels do not need to prevent them from being widely used to understand long-term buying behaviour. The suitability of such continuous panels will depend on the category being investigated, the research intent, and the analytical approach. Regardless, it is essential for analysts to be aware of these panel sample selection effects and the potential influences on results. When evaluating a continuous panel, we recommend exploring differences with the full panels in terms of composition, time-series trends, and brand loyalty.

An analyst needs to consider how their filtering process for continuous households changes the panel composition relative to the full panel, and by extension the representativeness of the market population. This should entail comparisons of key demographic characteristics (e.g., ages, household size, income) and shopping behaviours (e.g., shopping frequency, spend per trip). In addition, consideration also needs to be given to how the continuously reporting households change over time. For example, changes in the household incomes and household size.

Due to the differences in sample composition, full and continuous panels may not always be expected to match on absolute measures (e.g., penetration level). However, it is important to investigate whether observed purchasing trends are at least correlated between the continuous and full panels. This is important for assessing the suitability of a continuous panel in its ability to explain real in-market trends. To provide an example of such tests, we compare the sales trends in a full panel and ten-year continuous panel (2007-2016) from the Nielsen Homescan data. Category-level trends are assessed for the total sales revenue (per 100 households) and the underlying components of category penetration (%), average category volume per buyer (e.g., lbs) and average category revenue per volume (e.g., $ per

lb). As examples, we present two contrasting examples: incandescent lamps (Figure 3) and
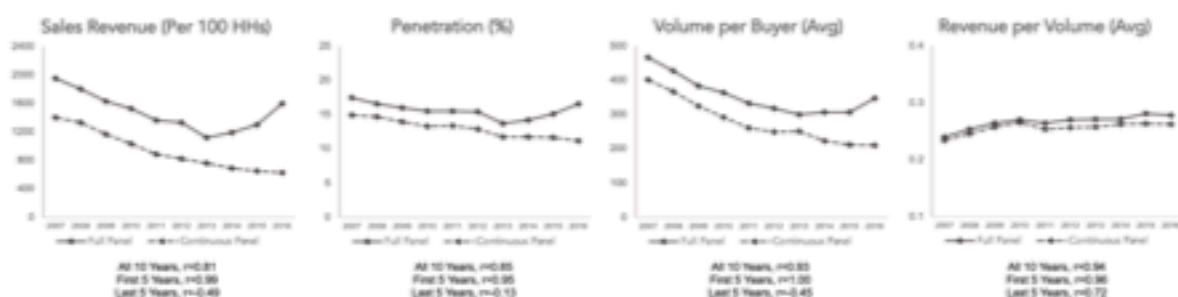
disposable diapers (Figure 4)

Figure 3. Full and continuous panel trends (Incandescent Lamps)
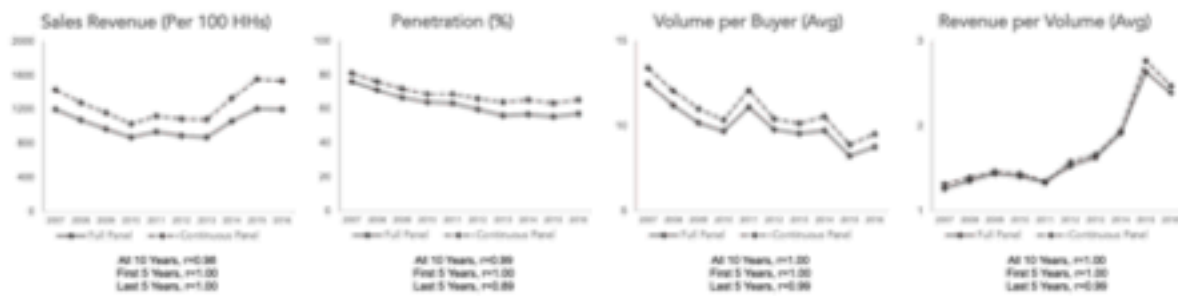
Data Source: Kilts Nielsen Consumer Panel Dataset 2007-2016, Continuous Panel (2007-2016): 17,054 panellists, Full Panel: c.62,000 panellists per year

Sales trends observed in the full panel for incandescent lamps closely mirror those

from the continuous panel. All sales and behavioural metrics have correlation coefficients

close to the value of 1 for the ten- and five-year periods. The only exception is penetration

which starts to diverge in the final years but is still strongly correlated over the last five years

(r=0.89). From this perspective, the incandescent lamps category is suitable for investigation

within a long-term continuous panel.

Figure 4. Full and continuous panel trends (Disposable Diapers)

Data Source: Kilts Nielsen Consumer Panel Dataset 2007-2016, Continuous Panel (2007-2016): 17,054 panellists, Full Panel: c.62,000 panellists per year

Compared to incandescent lamps, the purchasing of disposable diapers is far more

likely to fluctuate as the reporting households go through different life stages (e.g., the birth

of a child). Figure 4 shows that the window of time when the continuous panel matches the full panel is much shorter, especially when it comes to penetration and volume per buyer. This highlights the limitation of using a continuous panel to investigate disposable diapers, if the purpose is to investigate market performance. However, the continuous panel may still be suitable if studying a cohort of consumers to understand how their purchase behaviour of the category evolves over time as they enter different life stages.

Finally, the analyst should consider whether continuous and full panels differ in their behavioural loyalty. Dawes et al. (2020) propose that remaining in a panel for long periods may be a sign of the household being more habitually loyal by nature. In line with Dawes et al. (2020), we compare the average share of category requirements across the panel types, using brands from the incandescent lamp and disposable diapers categories (Table 8). Similar average rates of loyalty can be seen for incandescent lamps, but slightly higher average share of category requirements is seen for the continuous panel with disposable diapers. Taking a continuous panel over a shorter period (2012 to 2016) helps to reduce this difference.

Table 8: Share of Category Requirements (Occasions)

	Avg. Share of Category Requirements (%)										
	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Avg.
Incandescent Lamps											
Full Panel	34	37	41	40	38	40	43	42	39	40	**39**
Continuous ('12 to '16)	-	-	-	-	-	39	41	40	38	39	**39**
Continuous ('07 to '16)	33	36	38	38	36	39	41	40	37	39	**38**
Average	**34**	**37**	**40**	**39**	**37**	**39**	**42**	**41**	**38**	**39**	**39**
Disposable Diapers											
Full Panel	27	29	27	26	30	30	29	28	30	30	**29**
Continuous ('12 to '16)	-	-	-	-	-	31	30	29	32	32	**31**
Continuous ('07 to '16)	28	32	29	29	33	33	32	31	34	34	**32**
Average	**28**	**31**	**28**	**28**	**32**	**31**	**30**	**29**	**32**	**32**	**30**

Data Source: Kilts Nielsen Consumer Panel Dataset, Only includes SCR for brands >1% market share

Continuous Panel (2007-2016): 17,054 panellists, Continuous Panel (2012-2016): 33,572 panellists, Full Panel: c.62,000 panellists per year

3.4 Summary – Methodological challenges

Long-term panel data can be analysed using a balanced sample of households in each year (full panel) or using smaller cohort continuously reporting households (continuous panel). A full panel is appropriate when analysing annual aggregate-level changes, but cumulative long-term repeat buying can only be investigated with a continuous panel.

The analysis of large, continuous panels holds much potential for developing new insights into long-term buying behaviour. However, analysts need to be cautious of using continuous panels that may produce misleading results due to sample selection effects. This is of greatest concerns for research or reporting metrics that attempt to explain trends and behaviour occurring within a market. When using continuous panels, it is important to interrogate how the filtering process has affected household composition, sales trends, and behavioural brand loyalty.

4. Summary and future research agenda

The increasing availability of long-run panel data provides a compelling opportunity for marketers to expand their planning perspective from the short to the long term. For marketers to use this type of panel data in the most effective and accurate ways possible, knowledge of long-term repeat-buying needs to be advanced from an evidence-based perspective.

In this paper, we have identified and illustrated some critical theoretical and methodological challenges associated with the application of these panels. Our initial analyses present novel findings and suggest new avenues to advance marketing science. We conclude the paper with a discussion of a future research agenda in the form of three overarching research questions.

4.1. How does market stationarity occur without stable purchase propensities?

Long-run near-stationarity in sales has been observed at the market share level with scanner data (Lal and Padmanabhan, 1995; Srinivasan et al., 2000; Dekimpe and Hanssens, 1995a) and is a predicted outcome of the class of zero-order models such as the NBD-Dirichlet (Goodhardt et al., 1984). A fundamental assumption underpinning these models is of stable purchase propensities, which results in market share equilibrium. However, when panel data is analysed over periods beyond a quarter or a year, the models reveal that stable share is generally achieved despite higher brand switching than assumed. That is, stable brands appear to maintain their market share only by achieving higher levels of cumulative penetration than even the NBD-Dirichlet predicts.

Research is needed to test, replicate, and extend existing empirical generalisations – the Laws of Marketing – under conditions of prolonged share equilibrium. This process involves using continuous panel data to investigate the evolution of cumulative penetration and loyalty over multiple years, and the existence of systematic pattern differences across conditions (e.g., brand size or category type). Any generalised patterns can provide marketers with long-term benchmarks and identify opportunities for model refinements.

Questions also arise as to why, where, and when consumers change purchase propensities. Analysis of long-term continuous data allows a broad enough lens to identify covariates of life stages (e.g., marriage, birth of children) and provides a new behavioural basis for investigating the long-term effects of different marketing interventions.

4.2. How do markets evolve over the long run?

The second set of questions concerns the temporal extent of market stationarity. The model assumption cannot be expected to hold indefinitely. A market can appear to conform to a condition of 'near-stationarity' within consecutive quarters or years. Over time, seemingly

minor deviations within each period can accumulate and alter the market structure (e.g., market shares, purchase rates). Two questions to address in long-term panel data are: over what time periods can market conditions be expected to substantially change, and under what conditions does this vary?

Using continuous panel data, our results demonstrated examples of NBD-Dirichlet goodness-of-fit tests over periods of one, five, and ten years. Overall, errors increased with time but not uniformly across categories. A fruitful avenue for future investigation would be to expand this research over many further categories, to better identify any potential covariates of non-stationarity. For example, are these changes in market structure the results of marketing interventions (e.g., levels of advertising, price changes, product innovation, building distribution) or due to specific category characteristics themselves? One obvious question is whether categories with proportionally more new buyers (e.g., disposable diapers with new families) may be more prone to market disruption from new brands and innovation compared to categories with mass appeal across age groups that are bought habitually.

Another avenue is to use continuous panel data to explore the long-run changes in repeat buying associated with brand growth and decline. As previously identified (Dawes et al., 2020), stationary brands experience erosion in long-term repeat buying loyalties which are offset by higher rates of attraction than expected. In our illustrations of non-stationary brands, declining brands fail to attract enough buyers to offset their rates of erosion. By contrast, growing brands appear to do so through maintaining rates of repeat buying and almost eliminating erosion. This novel approach to brand growth and decline warrants extensive replication as it has important strategic implications for brand management.

The NBD-Dirichlet is not a dynamic model, but it continues to provide a useful stationary benchmark for many common brand and category performance metrics against which emerging and long-run trends can still be evaluated.

4.3 How do categories grow and decline over time?

The third set of questions concern category dynamics. Category growth and decline have received little attention to date (recent exceptions include Dunn et al., 2019; Nenycz-Thiel et al., 2018b; Tanusondjaja et al., 2021), with the majority of marketing research focused on the brand level. Across our analysis of 50 categories, penetration and purchase frequencies remained relatively stable over a year or two. However, over periods of up to a decade, most categories experienced substantial expansion or contraction. Since this has positive or negative effects on competitive brand performance, future research effort should aim to expand initial findings and explore how far categories change over time, the patterns and persistence of this growth and decline, and antecedents of the changes.

As marketers' attention begins to focus on the longer term, analysis of category growth across more categories, countries, and conditions has the potential to reveal many managerially useful empirical generalisations. For instance, in our analysis, we have identified that categories change more in penetration than they do in purchase frequency. Further work in full, long-term, panel data might reveal the extent to which changes in category revenues across different conditions can be explained by changes in the number of people buying (penetration), how much people buy (volume per buyer) and how much they pay for what they buy (e.g., $ per volume) (Dunn et al., 2019). Knowledge of the behavioural underpinnings of category growth and decline will carry significant implications for manufacturers and retailers who increasingly aim to grow their categories to achieve brand sales increases.

Consequently, a further aspect of category growth and decline worthy of research in the new panel data is how evolution in category size or value affects changes in market share equilibrium. That is, do competing brands maintain their shares as the total size or value of the category expands or contracts? Potentially, category growth might be driven by the

actions of larger brands or collectively by smaller, innovative brands. Through using long-term continuous panels, research should explore how these shifts in consumer repertoires over time have a cumulative effect on the total category volume and value.

With attention to the theoretical and methodological challenges outlined in this paper, there will be much to discover in long-run panel data that can usefully advance knowledge of the long-run impact of marketing investment and shift the focus from short term performance to long term outcomes.

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