Marketing research faces two challenges and a world of opportunity with long-term panel data

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Abstract

There have been frequent calls in the literature for a more comprehensive understanding of marketing impact on long-term firm performance (Dawes, Meyer-Waarden, & Driesener, 2015; Hanssens & Pauwels, 2016; Lodish & Mela, 2007; Webster & 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 sales dynamics. Now that far larger extended household panels are available, there is, for the first time, a valuable behavioural lens with which to observe long-term brand and category buying. In this paper we outline theoretical and methodological challenges to this new type of panel research. The first concerns an approach to extending established marketing theory to long-run repeat buying; the second relates to the inherent constraints of long-term panels. We present a new research agenda to progress explanatory theories of long-run brand building and category growth in this new but largely untapped resource.

Keywords

Household Panel Data; Long-Term Repeat Buying, Market Stationarity; Category Growth

Acknowledgements

Researchers own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analysing and preparing the results reported herein.

Introduction

Marketing management remains under pressure to demonstrate long-run impact from its considerable annual budgets (Binet & Field, 2007, 2013; Hanssens & Pauwels, 2016; Lodish & Mela, 2007; Webster & Lusch, 2013). Understanding the linkages between sales outcomes achieved within a quarter or a year and persistent sales effects over five years or more is thus a growing focus of academic research (Ataman, Van Heerde, & Mela, 2010; Leeflang et al., 2009). In this domain, retail store scanner data has long been the staple empirical source. Its continuous nature is its strength, because it lends itself to time series analysis of sales effects, sometimes over decades, from which an understanding of the likely long-run sales impact of marketing mix interventions is emerging (Dekimpe & Hanssens, 2000; Dekimpe & Hanssens, 2010).

This is important knowledge. For example, evaluating just one or two quarter's sales results might give the impression that price promotion is a critical tactic for brand growth. Certainly, top line effects are often dramatic. Yet, study of short and long-term marketing mix elasticities over five years has revealed that the relative effects of price promotion are less than those for changes in advertising, distribution and product line length (Ataman et al., 2010). Analysing scanner data spanning close to two decades has even allowed modelers to examine how changes in the business cycle impact marketing mix effectiveness (Van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013), but perhaps one of the more striking findings has been that for the majority of CPG brands, market share is expected to remain persistently stationary despite the short-term fluctuations that result from marketing activities (Dekimpe & Hanssens, 1995).

Although retail scanner data is useful for modelling long-run sales trends, it has a major limitation in not explaining the behavioural shifts underlying those sales 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. Purchasing records from household panel data are required to add behavioural insight to the understanding of sales response.

One of the most valuable purchase behaviour metrics that can be derived from household panel data is penetration. Brand share and *all* behavioural loyalty measures are highly correlated with brand penetration (Ehrenberg, Uncles, & Goodhardt, 2004; Sharp, Wright, Kennedy, & Nguyen, 2017) and therefore one common feature in all sales dynamics is likely to be *a change* in penetration (Riebe, Wright, Stern, & Sharp, 2014). Penetration has long been the basis for many managerially useful empirical generalisations and explanatory theories of market structure and behavioural loyalty (e.g. The Law of Double Jeopardy Ehrenberg, Goodhardt, & Barwise, 1990), household brand repertoire development (e.g. Stocchi, Banelis, & Wright, 2016; Trinh, 2014) and the extent to which brands and SKUs share their customers with competitors (e.g., Tanusondjaja, Nenycz-Thiel, & Kennedy, 2016).

These empirical generalisations and the theoretical assumptions that support them are often referred to as Laws of Marketing (Sharp, 2010), and together they define how brands grow. There is ample motivation to generalise or extend the laws to the long term. One is to progress robust evidence-based knowledge of brand building; a second is to better understand category growth. 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 here too penetration is important for growth (Dunn, Nenycz-Thiel, McColl, Martin, & Tanusondjaja, 2019; Nenycz-Thiel, McColl, Dawes, Trinh, & Graham, 2018).

Reliable and continuous household panel data was until recently, only available in annual or bi-annual slices, limiting the scope for long-term research. Far longer runs of panel data with larger samples sizes are now available to managers and researchers, and they offer an intriguing extended view of buying behaviour. An example of this type of data from the United States is the Nielsen Homescan Consumer Panel Dataset, which has been made available for academic research via the Kilts Centre of Marketing (Kilts Centre for Marketing, 2019). This is a longitudinal database starting in 2004 and is updated annually. For each year of the data, approximately 40,000-60,000 demographically balanced households have provided a continuous record of their purchases across different channels and retailers (Nielsen, 2015). The datasets include household purchases from more than 1,000 different food and non-food product categories (pre-defined by Nielsen as “modules”), comprised of around 1.5 million unique UPCs. This type of data presents analysts with two new challenges, one theoretical and one methodological.

The *theoretical* challenge concerns the need to examine how established marketing laws will continue to explain repeat-buying outcomes over a strategic time frame. The challenge here is to extend existing knowledge in such a way that it connects short to long term and identifies whether and when length of time may act as a boundary condition. We present early findings from several long-term datasets to illustrate this challenge and discuss a promising line of attack for the future. The second set of challenges are *methodological*: they relate to the fundamental considerations and limitations in approach that researchers will face when analysing household panel datasets covering many years of continuous buying. We summarise these as a set of new research opportunities that will inform various dimensions of the same problem. We conclude by bringing the two challenges together in the form of a future research agenda.

Theoretical Challenge - Understanding long-run repeat-buying

Knowledge of repeat purchase loyalty is robust over a few quarters. Models such as the NBD (Ehrenberg, 1959; Goodhardt & Ehrenberg, 1967), the NBD-Dirichlet (Goodhardt, Ehrenberg, & Chatfield, 1984), and the Pareto/NBD (Fader, Hardie, & Lee, 2005; Schmittlein, Morrison, & Colombo, 1987) have become generalised in theory and widely adopted in practice over this time span. 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'. Robust empirical support for stationarity has been developed using household panel data aggregated at monthly, quarterly or annual levels (Ehrenberg, 1988; Ehrenberg et al., 2004).

An important feature of the "mechanics" of repeat buying, but one not widely acknowledged, is the time dependency of penetration and average purchase frequency. To illustrate, if observed brand performance remains stationary from one quarter to the next, but only a proportion of quarter-one buyers repeat in quarter two, then over six months the size of the *cumulative* customer base has grown. In the same time, although the purchase frequency of repeating buyers has necessarily increased, many of the "new" buyers will buy only once in the second quarter, suppressing the rate of growth in the six-monthly mean purchase rate. As the length of time widens, both cumulative measures can be expected to increase further.

The class of zero-order models identified above will project cumulative performance measures (including inter-period repeat, drop-out, and attraction rates) across periods of any length. To do so, they assume among other things that over time no further consumer learning occurs, that brand and category buying rates will remain independent, and that shopper brand preferences will not change, so brands continue to enter individual household repertoires, but only in line with established propensity distributions. Given that the whole purpose of marketing is to break every single one of these assumptions, the stationary condition that holds over a year or eighteen months might reasonably be expected to be only temporary. Few studies have yet investigated how robust the projections and therefore the theoretical assumptions of these models remain to extended category or brand performance (some exceptions are Stern & Hammond, 2004; Trinh & Anesbury, 2015).

There is nevertheless extensive evidence for long run near-stationarity in market share (the sales outcome of fixed purchase propensities) from retail scanner studies. For example, Lal and Padmanabhan (1995) observed that three in five brands were stationary over nine years, Srinivasan *et al* (2000) found a similar result over seven, and Dekimpe and Hanssens (1995) reported no trend in around eight in ten share-series from a meta-analysis of over 400 studies. But these sales outcomes do not take account of underlying repeat-buying, and the implications of long-term penetration growth pose intriguing questions for marketing about the cumulative value of behavioural loyalty and the nature of long-term brand building. Larger household panel datasets now therefore present researchers with the first of our two challenges; to extend understanding of continuous brand and category repeat-buying. In the following sections, we first suggest how long-term panel data can be analysed to reveal the behavioural underpinnings of long-run stationarity. We then present several analyses that reveal when, and the extent to which, existing knowledge of consumer behaviour begins to reach its boundary conditions.

Understanding long-term repeat buying under stationary conditions

The first example is in time series, observations and model output of repeat buying performance metrics in a typical strategic window of twenty quarters for a single brand, a leading UK laundry detergent. 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. Brand share performance in the short term is volatile but off-setting (Graham, 2009), so following (1989), the signal to noise ratio in the data has been smoothed to report the mean value of each of the four quarterly-metrics for each year. Brand share performance is then seen to be at least near-stationary. Over five years the relationship between penetration and purchase frequency, the sales equation, also remains typical of any brand constrained by the established Law of Double Jeopardy (Dawes, 2016; Ehrenberg et al., 1990). That is, the share-change is associated more with penetration than with purchase frequency, so the evidence here is consistent with the Laws of Marketing, at least in cross sectional data (but see Albuquerque and Bronnenberg (Albuquerque & Bronnenberg, 2009) and Dawes, Meyer-Waarden & Driesener (2015) for replications and extensions of this effect).

Table 1: Near-stationary quarterly brand performance over 5 years

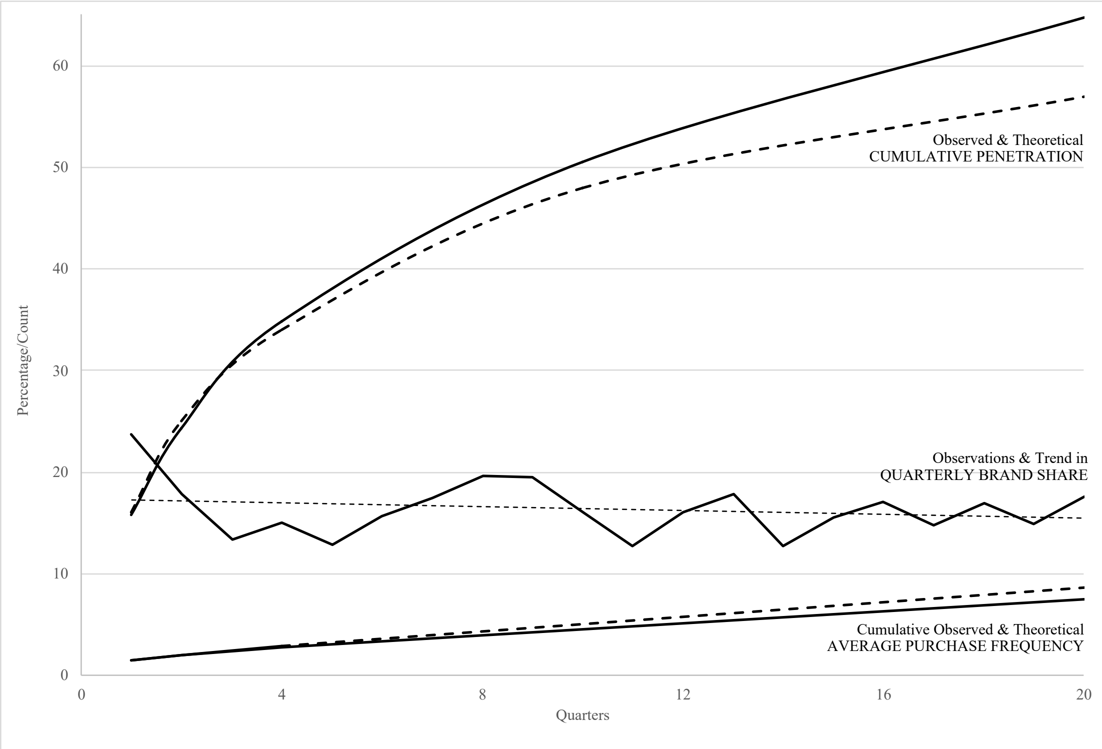
Average Quarter…	Brand Share	Penetration	Purchase Frequency
In Year 1	18	18	1.5
In Year 2	16	16	1.5
In Year 3	16	16	1.5
In Year 4	16	15	1.5
In Year 5	16	14	1.5
Average	**16**	**16**	**1.5**

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

Of course, in equilibrium, market share metrics (the relative proportion of total sales) remain constant in aggregations of quarter, a year, or even five years. To determine more clearly what then happens as sales grow, brand share was plotted against *cumulative* penetration and purchase frequency outcomes from a notional "first" quarter in Year 1. The plot (Figure 1) shows how over time, stationary share depends upon a dramatic increase in the size of the customer base *and* a steady growth in repeat buying. However, the penetration required to maintain that stationarity evolves dramatically, doubling from 16% to 35% by the end of the fourth quarter. Although its penetration growth slows, the brand had reached ***two-thirds*** of the panel by the end of the fifth year. Average purchase frequency increased linearly by contrast, from 1.5 packs in a quarter to 2.8 in a year and so on.

To determine how closely existing assumptions of repeat buying accounted for this evolution, NBD estimates provided theoretical comparators (shown as dotted curves). These were found to be close to observed values, but with progressive deviations emerging as the period of observation widens. Successful NBD estimates to annual data are not new (Morrison & Schmittlein, 1988; Schmittlein, Bemmaor, & Morrison, 1985), but the extension reported here shows that NBD theory could generally predict a bigger story quite well: the very substantial scale of penetration growth necessary over time to maintain a long-run stationary share.

Figure 1. UK Detergent. NBD predicted & observed cumulative sales equation



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

As a reminder, the metrics reported are those for an established and leading brand. The managerial implications are therefore significant, namely: (1) half of the brand's ultimate buyers did not buy it *at all* in year one; (2) a high rate of attraction is constantly required to maintain a stationary share (3) a very large proportion of the "new" consumers must be extremely light buyers of the brand; (4) the stability of quarterly or annual performance metrics (e.g. Table 1) may easily give a misleading view of the scale of the tasks involved in long-run brand building; and (5) if the Double Jeopardy relationship is maintained in cumulative performance, then outcomes for smaller brands (with even lower loyalty) will depend far more on acquiring buyers than even this analysis represents. Each of these five points raise questions for further research, because a more comprehensive knowledge of the relationship between short- and long-term performance could then be obtained.

If a model such as the NBD generalises to the long term then questions of consistent buyer behaviour between quarters or years are also implied. In stationary markets, managing loyalty is a common strategic focus, so the future behaviour of any group of buyers based on their current behaviour is of great interest – managers will certainly want to manage their most valuable buyers for example. But over successive periods in the stationary condition, individual-level behaviour does not appear to be quite so "manageable". When Romaniuk and Wight (2015) tracked repeat buying rates of the heaviest brand buyers from one year to the next they found that only about half remained heavy in the subsequent year, yet with no loss of brand share. Their findings demonstrate an inherent danger in targeting based on annual sales. The effect is brought about by the regression to the mean of stochastic purchase timing and the consequent buyer flows are predictable (e.g., Trinh, Rungie, Wright, Driesener, & Dawes, 2014), but only, so far, from one year to the next. More work is needed to extend this type of buyer flow modelling.

In addition, the analysis in Figure 1 represents only one behavioural loyalty metric, average purchase frequency. Dawes, Meyer-Waarden & Driesener (2015) report three further loyalty metrics common in CPG modelling, and in practice. They include *phi* – a switching parameter; share of category requirements (SCR); and repertoire size. In annual cross-sections of up to eleven years these share-based loyalty measures were found to remain near-stationary, but if measured cumulatively, they too would be sensitive to rates of penetration growth and continuous customer churn.

Finally, it is also clear from Figure 1 that brand performance cannot be entirely stationary. Over five years, the NBD has underestimated penetration (by as much as 18%) but over-estimated loyalty by a purchase or so. If non-stationarity extends to rival brands and/or to category buying then the bias indicates higher switching than anticipated, posing additional questions about the distribution of brand choices across repertoires. The surprise in this data is hardly that brand performance is a little dynamic, but that over five years and many millions of purchases it remains as stable as it does, given that a brand of this size must eventually reach not one third, but *two thirds* of all UK households. This behavioural view of share equilibrium is novel, to the extent that our understanding of marketing may need re-evaluation. New types of panel data open the door to further research, testing the laws of marketing and their related theory. The real benefit of working in this way, rather than attempting to create new theory, is that the extensions discovered then intuitively link long-term outcomes to short term decision making, with very powerful managerial implications.

Reaching the boundary conditions of the stationarity assumption

Consumers' purchase propensities may not change much over a year or so, but may start to alter over far longer periods as households go through different life stages (e.g., entering adulthood, getting married, starting families, income changes, retirement) and as brands and products evolve incrementally from technological advances (Sharp et al., 2012). The NBD fitting in Figure 1 reflects findings in a study by East and Hammond (1996) that examined repeat purchase loyalty. Over six successive quarters they reported a systematic erosion of repeat purchase loyalty for competing brands in several countries and categories against the stationary NBD benchmark. With no loss of market share recorded, this means that the brands were "topping up" sales by attracting additional buyers beyond prediction. Further research in long term panel data is now possible to identify the extent of this non-stationarity and, importantly, the relative strength of any of its covariates, including promotion intensity, new product introductions or other marketing mix investments. If continuous panellists are sampled, then covariates in life-stage variables could also be explored. Findings here would then demonstrate the influence of marketing mix interventions on established consumer behaviour.

This work would then benefit from a more parsimonious modelling approach. In repertoire categories if underlying brand performance metrics are non-stationary in the context of long-run market share equilibrium, then that non-stationarity must be reflected across the performance metrics of competitors also. A useful model in identifying this is the NBD-Dirichlet (Goodhardt et al., 1984). It shares the zero-order assumptions of the NBD on which it is built and, its authors noted, the ability to extend predictions in time. A special feature is that it predicts performance metrics simultaneously for all nominated competing brands in a category from just a handful of metrics. Sharp et al (2012) give a useful description of its many advantages and applications, but in the novel field of long-term analysis, because the assumptions of the Dirichlet support the many empirical generalisations and laws of marketing science, its estimates can quickly establish the robustness of theory over multiple years and in cumulative aggregations.

As an example, Table 2 shows this new type of NBD-Dirichlet fitting to a product category, Aluminium Foil, over periods aggregated at one, five and ten years. Data is from a US household panel of continuous reporters. At one year, the observed (O) and theoretical (T) values show a close fit across all brands. The two leaders, *Brand A* and *Private Label*, show a similarly close fit even when the time period is expanded to five years, and fit is, astonishingly, also maintained over ten years. However, greater deviations between observed and theoretical values begin to emerge for smaller brands as the analysis window is expanded, and it is also clear that the relationship between penetration and purchase frequency also changes in nature between large and small brands. The range of purchase frequency values widens in extended aggregation. The fitting suggests that small brand share will depend on attracting many more, and far lighter buyers than even Double Jeopardy theory predicts, and therefore now prompts investigation of the contribution of behavioural loyalty to long-run brand building outcomes.

Table 2: Aluminium Foil NBD-Dirichlet Benchmarks up to 10 years

	1 Year (2007)				**5 Years (2007-2011)**				**10 Years (2007-2016)**			
	Penetration		Purch Frequency		Penetration		Purch Frequency		Penetration		Purch Frequency	
	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 Brands	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**

Data Source: Kilts Nielsen Consumer Panel Dataset, 2007 to 2016.
Aluminium Foil Product Module: c.17,000 continuous panellists

Although highly informative in describing the characteristics of a brand's "total" long-run customer base, cumulative analysis of this type masks the detail of any individual brand dynamics. For example, in time series, *Brand B* declined from a 5% share brand in 2007 to less than 1% in 2016. Further analysis then becomes necessary to compare cumulative outcomes with cross-sectional non-stationary performance. The aim is to understand how the laws of marketing apply as brands fall out of favour or increase in size, in their competitive context. Long term data thus provide analysts with richer and more granular material to develop a comprehensive extended view of share trajectories and offer a greater number of exceptional cases for study, in order to identify emerging boundary conditions

The NBD-Dirichlet authors, and others, later (Dawes, Kennedy, Green, & Sharp, 2018) always proposed that its main use is in benchmarking significant sameness in many sets of data (MSoD) rather than significant difference in a single set. Statistical significance may even be obsolete (Kennedy, Scriven, & Nenycz-Thiel, 2014) where strong patterns and regularities are clearly revealed over many datasets. But in order to establish a boundary condition to theory, it is necessary to *draw* some tentative boundary, no matter how speculative.

A set of goodness-of-fit statistics for Dirichlet estimates of penetration and purchase frequency have been proposed by Driesener *et al* (2017) which may be useful when prompting questions about boundary conditions in long-run analyses. Those authors point out that a Dirichlet fitting is not assessed on its estimates of a single brand performance, but on *"how well the model fits the category as a whole"* (p.289) usually by evaluating deviations between estimated and observed values over the arrays of data on each metric when tabulated as in Table 2. Four tests have historically emerged for this: Pearson's correlation (Correl); the relative difference between the column averages (AVE); absolute deviation relative to the average (RAAE); and the mean absolute percentage error (MAPE).

To demonstrate, we extended the Aluminium Foil analysis, replicating it in the same time windows in four additional categories, Chewing Gum; Margarine and Spreads; Toilet Tissue; and Frozen Bagels. Column averages in Table 3 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 is therefore unlikely to present a consistent boundary condition to repeat-buying effects on market structure.

Table 3: NBD-Dirichlet Goodness-of-fit up to 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. c.17,000 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%

Category conditions

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 & Pilon, 1980; Nijs, Dekimpe, Steenkamp, & Hanssens, 2001; Pauwels, Hanssens, & Siddarth, 2002) but if, as Table 3 suggests, certain categories violate Dirichlet assumptions more than others over longer time periods, the explanations could relate either to marketing activity or to external category conditions, or to both. Leeflang et al (2017) categorise reported disruptors of category level equilibrium, as technology diffusion, macro-economic forces, feedback loops in consumer and trade behaviours, and asymmetric competitive response, all of which might lead to slow moving category-level dynamics in penetration or purchase frequency that would be missed in short term analyses. In addition, stationarity in sales might not mean stationarity in underlying repeat buying. Ehrenberg et al (2004) consequently called for further Dirichlet analysis of long-term category-level trends (p.1315) and this is now possible in the new forms of panel data.

We 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 4).

Table 4: Change in annual penetration and average purchase frequency (n=50 categories)

	Penetration			Average Purchase Frequency		
Changes from 2007 to:	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.60,000 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 is extended, the changes quickly accelerate. After three years (just beyond the usual view of repeat-buying in panel data), 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 changes over more 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. 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 can a single brand grow a category? And further, are there consistent, generalisable patterns in how categories grow and decline?

To summarise, the new panel data presents an important theoretical challenge to researchers, to progress understanding of long-run repeat-buying from empirical evidence rather than from assumption. The opportunities for marketing science to extend knowledge of the patterns and regularities of behavioural loyalty and competitive market structures open many doors to connect long and short-term marketing outcomes. However, the broad scope of the data introduces new and important methodological challenges, which if not addressed, might potentially lead to misleading conclusions. Therefore, in the next section, we list some of those considerations and provide empirical illustrations.

Methodological Challenge - Analysing panel-data over the long-term

In addressing the theoretical challenges in long run panel data, careful consideration must first be given to the sample elements. Regardless of its total length, household panel data is generally provided in shorter periods of years or quarters. Between the periods, the panel composition changes 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 households in each year (full panel) or from a sub-set of households that have continuously reported purchases over the period of analysis (continuous panel). Both of these approaches have limitations, which is true of all data types regardless of the field of study. The only way to progress is to be aware of those limitations and potential sources of bias.

Evaluating Full versus Continuous Household Panels

Household panels are quota sampled with efforts made around replacement and attrition to provide demographically and geographically comparable panellists between periods. The full panel approach is suitable for analysing long-run changes in aggregate-level behavioural metrics. For instance, the analysis of category-level penetrations and purchase frequency changes over nine-years that were presented in Table 4. Full panels have commonly been used to investigate dynamics in brand loyalty patterns over time (Casteran, Chrysochou, & Meyer-Waarden, 2019; Dawes et al., 2015; Johnson, 1984).

While full panels can provide valuable behavioural insights, the major limitation is the inability to assess long-run individual-level repeat buying behaviour. As was observed in Table 1 and Figure 1, brand performance metrics can appear stable while at the same time individual repeat buying rates do not conform to expectations given market stationarity. 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. Among the few studies that have used continuous panels, these have been used to investigate long-run brand performance (Graham, 2009), consumer loyalty (Stern & Hammond, 2004) and long-term effects of marketing interventions (Jedidi, Mela, & Gupta, 1999; Mela, Gupta, & Jedidi, 1998; Mela, Jedidi, & Bowman, 1998). In this paper, we have used continuous panellists to contrast NBD-Dirichlet fits over periods of one, five and ten years (Table 3).

An issue with using continuous panels has historically been the reduction in sample size that occurs in the filtering process. Smaller panel samples can risk sample error even for medium sized brands and lightly bought categories. However, panels now often contain tens of thousands of panellists; the US Nielsen Homescan Consumer Panel used here for example has approximately 60,000 households reporting each year from 2007. Even when the panel is filtered for continuous reporters over a ten-year time span (2007-2016), a sample is still returned with more than 17,000 households.

Sample error aside, the data from continuous panels may still be prone to certain biases, especially as windows of observation widen. The full panels are matched year to year to be demographically comparable, yet demographic change in unavoidable when tracking a continuous group of panellists over time. Most notably, the continuous panel will age over the period of analysis. For instance, with a ten-year continuous panel, the panellists will be ten years older in the final year compared to the first year. This makes it difficult to disentangle long-term market trends from life-stages effects. For instance, Trinh et al (Trinh, Wright, & Stern, 2014) identify a U shape loyalty response curve with younger and older households being rather more loyal. In addition, changing life stages (e.g., entering adulthood, marriage, starting a family, retirement) may influence the types of categories and brands used and their frequency of purchase. Effects over ten or more years may become quite pronounced for a fixed sample.

A continuous panel may also be disposed to underestimating measures of cumulative penetration over time due to the nature of a fixed sample. In reality, younger consumers will enter the market at different points in time as they transition to adulthood, while older consumers will leave the market due to mortality. If households need to be present in all years of analysis, this will likely lead to an underrepresenting older consumer in the earlier years and younger consumers in the later years. Similarly, a continuous panel will not account for migration to and from different regions. Finally, panel data is analysed at the household level, but household composition is likely to change with time, meaning the range and types of brands chosen is likely to fluctuate with the passing years. These biases will increase with time and limit the length of observation that can be analysed with continuous panellists, although this may be category specific (e.g., whether category is bought more/less frequently by different age groups).

Due to the differences in sample composition, full and continuous panels cannot always be expected to match on absolute measures (e.g. penetration level). However, it will be important to investigate whether trends are at least correlated between the two panel types. For instance, are the long-term buying behaviours of continuous reporters likely to reflect the wider consumer base?

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. Across the same 50 categories reported in Table 4, we assess category-level trends across four metrics:

- Category Sales Revenue
- Category Penetration (%)
- Average Category Volume per Buyer (e.g. lbs)
- Average Category Revenue per Volume (e.g., $ per lb)

To adjust for changes in panel size between the panel types and between years in the full panel, we adopt a standardised measure of Sales per 100 Households for Category Sales Revenue. Table 5 reports the average correlations across categories for all four metrics. The correlations assess the average annual changes observed in the full versus the 10-year continuous panel over (1) the full ten years, (2) the first five years and (3) the final five years.

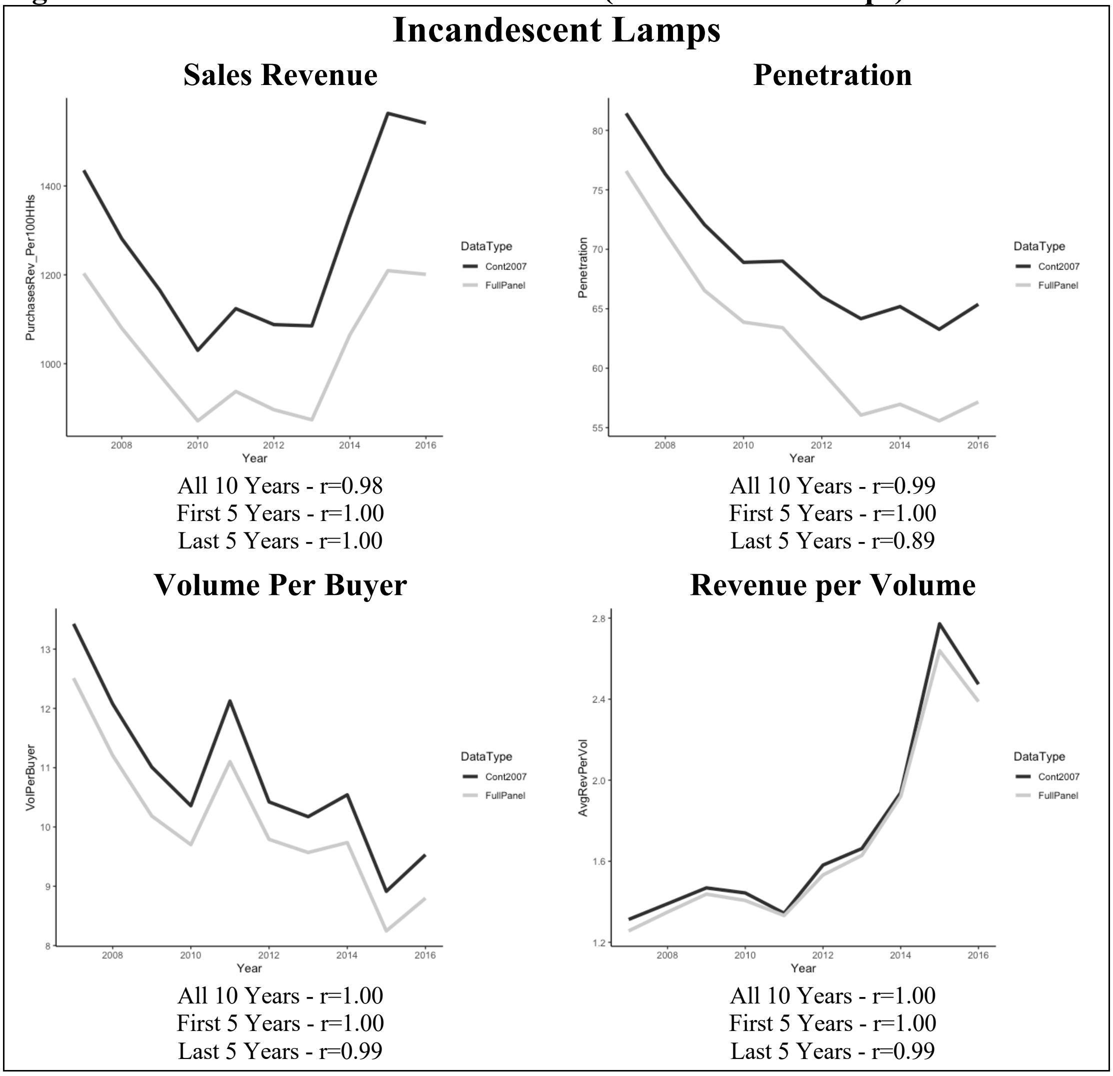
Table 5: Full and Continuous Panel average correlations, 2007-2016 (n=50 categories)

	Category Sales Revenue	**Category Penetration**	**Category Average Vol. per Buyer**	**Category Average Revenue per Vol.**
All 10 Years (2007-2016)	0.87	0.88	0.83	0.98
First 5 Years (2007-2012)	0.91	0.91	0.80	0.97
Last 5 Years (2012-2016)	0.77	0.78	0.75	0.91

Overall, similar patterns of category growth and decline are observed from the full and continuous panels. For total category sales revenue, there is a strong positive correlation (r = 0.87). When the sales are decomposed, the trends from two panel types are still quite consistent across the other three metrics. However, there is a notably stronger correlation with revenue per volume changes (r = 0.98) than with either penetration (r = 0.88) or volume per buyer (r=0.83). The consistency between full and continuous trends is also greater in the first five years of analysis than the later five years. While all metrics show this pattern, the difference in total sales revenue (r=0.91 vs r=0.77) appears to be predominantly due to differences in penetration trends (r=0.91 vs r=0.78). This indicates that there may be time-bound limits to how representative continuous panels are of the wider industry trends.

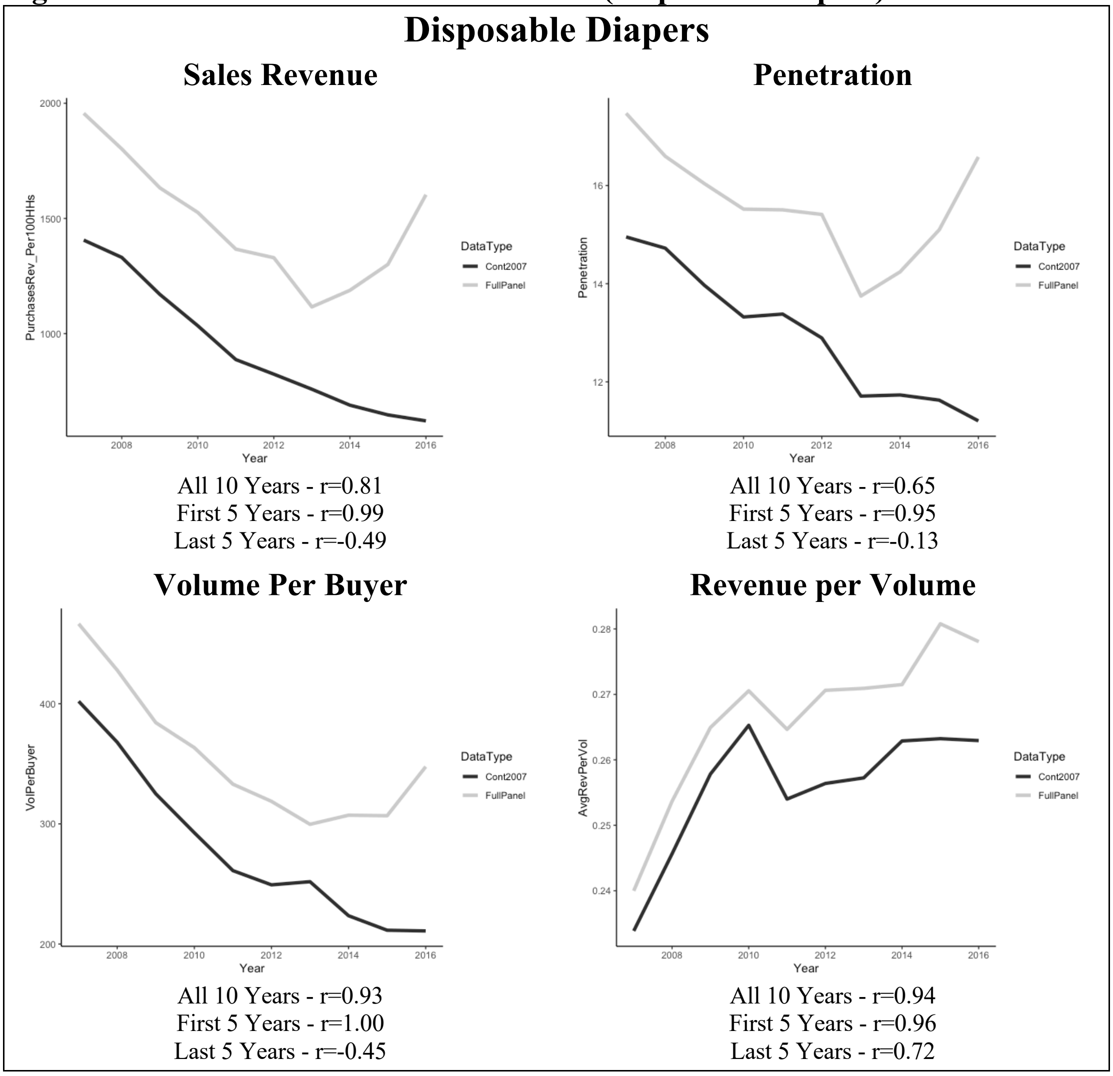
While the overall results in Table 5 demonstrate reasonably consistent trends between full and continuous panels, there are individual differences between product categories. We present two contrasting examples incandescent lamps (Figure 2) and disposable diapers (Figure 2) to illustrate this.

Figure 2. Full and Continuous Panel trends (Incandescent Lamps)



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). Therefore, the incandescent lamps category is suitable for investigation within a long-term continuous panel.

Figure 3. Full and Continuous Panel trends (Disposable Diapers)



Compared to incandescent lamps, the purchasing of disposable diapers is far more likely to fluctuate as the households go through different life stages (e.g., birth of a child). As can be seen in Figure 3, the window of time that the continuous panel matches the full panel is much shorter, especially when it comes to penetration and volume per buyer.

The analysis of large, continuous panels holds much potential for developing new insights into long-term buying behaviour. However, continuous panels may not be suitable for analysing certain product categories over long-periods of time if they are particularly life-stage dependent. The suitability of a category or length of time should be determined by testing the consistency of key trends across the continuous and full panels.

Summary and Future Research Agenda

The increasing availability of long-term panel data provides new opportunities to understand the behavioural underpinnings of long-run brand and category performance. In this paper we have identified potential new streams of research and outlined key considerations and limitations for managers and analysts. Our initial analyses present novel findings and suggest new avenues for exploration to advance marketing science and knowledge of long-term repeat-buying from a new evidence-based perspective. We conclude the paper with a discussion of a future research agenda in the form of three overarching research questions.

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

Long-run near-stationarity has been previously observed at the market share level with scanner data (Dekimpe & Hanssens, 1995; Lal & Padmanabhan, 1995; Srinivasan et al., 2000) and is a predicted outcome of the class of zero-order models such as the NBD-Dirichlet (Goodhardt et al., 1984). A key assumption underpinning these models is stable purchase propensities, which then results in the market share equilibrium. However, when panel data has been analysed over periods beyond a quarter or a year, stable shares can be observed alongside greater brand switching than assumed. Stable brands appear to maintain their market share by achieving higher levels of cumulative penetration than the NBD-Dirichlet would predict.

There is a need to develop the behavioural view of what long-term repeat buying looks like under conditions of market share equilibrium. This involves using continuous panel data to investigate how cumulative penetration and loyalty evolve over multiple years, and whether there are any systematic differences in these patterns across conditions such as brand size and category type. Identifying new norms and a generalised understanding of those patterns could lead to model refinements. Questions also arise as to why consumers do not demonstrate stable purchase propensities. Potentially, this may be the expected long-term outcome of successful marketing activities, leading consumers to try new brands and modify their brand repertoires over time but with competitive effects cancelling out at the aggregate-level brand changes.

2. How long do markets remain stationary?

The NBD-Dirichlet and related models have an assumption of market stationarity, which have been found to hold well at least when looking over a quarter or a year. However, this assumption cannot be expected to hold indefinitely. An important question that can be addressed with long-term panel data is how long can markets be expected to maintain stationarity and under what conditions does this vary?

Using continuous panel data, this paper demonstrated examples of NBD-Dirichlet goodness-of-fit tests over periods of one, five and ten years. Overall, errors increased as length of time increased but not in a uniform manner across categories. A fruitful avenue for future investigation would be to expand this research over many more categories to understand the lengths of time different categories take before stationarity assumptions are violated, exploring potential co-variates of non-stationarity. For example, are these changes in market structure the results of marketing interventions that have been occurring (e.g., advertising, prices, product innovation, building distribution) and/or due to certain category characteristics? Research may examine 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. 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 be evaluated.

3. How do categories grow and decline over time?

Violation of stationarity at the category-level is an area worthy of its own stream of future research. Category growth and decline has received little attention to date (recent exceptions include Dunn et al., 2019; Nenycz-Thiel et al., 2018), with the majority of marketing research focused at the brand level. Across our analysis of 50 categories, penetration and purchase frequencies remained relatively stable over a year or two. However, over longer periods up to a decade, the majority of categories experienced substantial expansion or contraction. Future research should aim to expand this initial research to explore how much categories change over time, patterns of this growth and decline and antecedents of these changes.

Analysis of category growth research across more categories, countries and conditions has the potential to discover managerially useful empirical generalisations. For instance, in our analysis we have identified that categories change more in penetration than they do in purchase frequency, which is akin to the Double Jeopardy norm for brands (Ehrenberg et al., 1990). Building on this finding, further work could use full long-term panel data to explore the extent to which changes in category revenue sales across different conditions are explained by changes in the number of people buying (penetration), how much people are buying (volume per buyer) and how much they are paying for what they buy (e.g., $ per volume) (Dunn et al., 2019). Knowledge of the behavioural underpinnings of category growth and decline will have important strategic implications for manufacturers and retailers who increasingly aim to grow their categories in order to achieve brand sales increases.

Consequently, a further aspect of category growth and decline to be explored in panel data is how evolution affects (or is affected by) changes to the market share equilibrium. That is, do competing brands maintain their shares as the total size of the category, or its revenues expand or contract? Potentially, category growth may be driven by the actions of larger brands or, alternatively, collectively by smaller, innovative brands. If a category is premiumising (i.e., increasing $ per volume), this will likely be seen through a shift to higher priced brands. Through the use of long-term continuous panels, research should explore how these shifts in consumers repertoires over time have a cumulative effect on the total category.

There is a great deal for researchers and managers to usefully discover from long-run panel data about the long-run impact of marketing investment. We have discussed two challenges that any analyst must face, but given the volume of data and the scope for complexity inherent in multi-year analysis, a useful starting point for that work may perhaps still be found inside the front cover of Andrew Ehrenberg's *Repeat-Buying* (1988) where he wrote:

> *Of the thousand and one variables which might affect buyer behaviour, it is found that nine hundred and ninety-nine usually do not matter. Many aspects of buyer behaviour can be predicted simply from the penetration and average purchase frequency of the item, and even these two variables are interrelated.*

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