**Double Jeopardy - 50 years on.**

**Reviving a forgotten tool that still predicts brand loyalty**

**1. Introduction**

Scientists aim for their studies' findings to be replicable. An experiment testing ideas about the rate at which consumers buy shampoo brands should yield the same results when repeated in different times or countries. Similarly, two different researchers studying capital goods buying-behaviour in the same way should come to the same conclusions regarding its measurements and composition. Through the scientific process of replication, researchers aim to reconstruct the unchanging rules by which the universe operates - rules that hold everywhere, perhaps within limits or boundaries, but regardless of who is studying them. If a finding can't be replicated, it suggests that current understanding or methods of testing are insufficient.

The process of science doesn't require that *every* experiment and *every* study be repeated, but that many should be, especially those that produce surprising or important results. In some fields, it is standard procedure for scientists to replicate their own results before publication in order to ensure that the findings were not due to some fluke or to factors outside the experimental design (Uncles & Kwok, 2013).

The desire for replicability is one reason that scientific papers include a methods section that describes exactly how the researchers performed the study, defining concepts, measures and operational procedures. That section allows other researchers to replicate the study, to evaluate its quality, and perhaps improve the method or to extend the knowledge base. An empirical generalisation may then emerge which summarises results from repeated empirical studies to the extent that the scientists have confidence that the same pattern or relationship will recur in future tests. Ultimately, enough evidence may accumulate for this to support a statement to the effect that the scientist considers it a statement of fact, the truth, or a law. Replication is the key to identifying laws and the empirical generalisations that summarise them, and to establishing their extent, limitations and conditions in which they do not apply.

*1.1 Research Questions*

This research was undertaken in the spirit of continuously subjecting laws to differentiated testing. It is focussed on the most useful empirical generalisation in marketing, the Law of Double Jeopardy (Ehrenberg, Goodhardt, & Barwise, 1990). This law has been extensively tested over thirty-five years or more, and rightly so, since it provides a key to the multi-million dollar question of how brands grow. When Double Jeopardy constrains choice behaviour, marketers should know that brand share growth depends on substantially increasing the size of the customer base rather more than on managing customer loyalty (Sharp, 2010; Trinh & Anesbury, 2015).

Every marketing environment is however in flux. Conditions under which this law has not yet been tested may have become more significant, while others that are already critical may only become observable as improving technology gives access to better data. The aims of this paper are thus two fold; first to extend the boundaries of the law by assessing it under new or little tested conditions, and second to revive interest in the now somewhat overlooked mathematical derivation of Double Jeopardy, in order to compare predictions from its *w*(1- *b*) approximation with the output of the more widely adopted NBD-Dirichlet (Goodhardt, Ehrenberg & Chatfield, 1984).

Repeat purchase loyalty receives a great deal management attention. Brands build shareholder value by delivering repeat purchase over the long run, but some have warned that short-term management and wider consumer choice is leading to a long-term decline in loyalty (Binet & Field, 2015; Dawes, Meyer-Waarden and Driesener, 2015; Lodish and Mela, 2007). The first research question (RQ1) here was to evaluate three effects of time on Double Jeopardy choice behaviour; first in cross-section, replicating fittings presented in Ehrenberg Goodhardt and Barwise (1990) with more recent data from different countries; second using six-year continuous buyer panels to estimate the long-run outcomes of the Double Jeopardy constraint; and last in replications of Consumer Packaged Goods (CPG) categories pre-and post-internet grocery shopping.

Then, non-western markets are important sources of growth for brands facing market saturation, but the dynamic conditions brought about by new buyers and new entrants challenge the underlying assumptions of zero-order models, which may not then provide usable insight. The next question (RQ2) was to test the boundaries of the law through replications in non-western market conditions.

Double Jeopardy has been most commonly tested at the brand level so the third question was to evaluate its operation in two previously untested category aggregations (RQ3), long term capital goods buying and at a house-of-brands level, where firms manage brand portfolios as a strategy to combat market equilibrium.

Ehrenberg Goodhardt and Barwise (1990) and Ehrenberg and Bound (1993) credited the development of the *w*(1-*b*) approximation to Goodhardt and Chatfield, showing how closely it estimated normal levels of repeat-purchase loyalty. For managers (and academics) it is easily applied using a handful of common data and a spreadsheet, and yet over the past twenty-five years has attracted surprisingly little attention. An empirical generalisation becomes useful if it provides performance benchmarks, but Barwise (1995) suggested that a *good* empirical generalisation should describe a relationship between variables with precision, and preferably mathematically. The last question (RQ4) was therefore to evaluate the goodness of fit of the *w*(1 – *b*) approximation against NBD-Dirichlet output in the new conditions studied here to demonstrate its continuing reliability and usefulness and encourage its use.

**2. Theory**

*2.1. Double Jeopardy*

The Law of Double Jeopardy identified by McPhee (1963) and elaborated in a repeat-buying context by Ehrenberg (1972;1988) states that behavioural loyalty differs little between competing brands of different sizes, but that smaller brands suffer twice (hence Double Jeopardy) in having fewer buyers who buy them a little less often.

Double Jeopardy (DJ) captures the predictable relationship between *w*, the average rate at which a brand’s customers buy it in a period and *b*, the proportion of the customers in the product-market who buy that brand at least once in the same time. While *b* varies greatly between competing brands, *w* varies very much less, and is usually closely in line with *b.* The fundamental finding in multi-brand DJ studies is the extent to which marketing management is constrained: there is no simple way to increase sales by persuading existing brand buyers to buy a brand more often (Ehrenberg, 1988).

In modelling CPG category structure, DJ is generally estimated using the NBD-Dirichlet, but an earlier and far simpler mathematical formula summarises the theoretical basis for the relationship and predicts expected purchase frequency for any brand in a category from its penetration without recourse to “heavy arithmetic” (Ehrenberg *et al.* 1990 p.86). The theoretical expression:

1. $w \left(1-b\right)≅a constant$

was reported in Ehrenberg, (1972;1988) demonstrated in Ehrenberg et al (1990) and expounded in Ehrenberg & Bound, (1993). Although it described observed repeat-buying behaviour closely, interest focussed on the subsequent development of the NBD-Dirichlet, probably because it captures a comprehensive range of metrics, and so little testing of the simpler algebra has been conducted since the mid-nineties.

*2.2 Knowledge, fads and empirical generalisations in the marketing environment*

It has been said that: *“The past is a foreign country; they do things differently there”* (Hartley, 1953).Certainly a great deal *was* different in marketing in the 1970’s and 80’s when Ehrenberg & Bound (1993 p.173) claimed that a DJ relationship in consumer choice behaviour had already been established in over 40 categories of food and drink, and in financial services, over the counter and prescription medicines, aviation fuel, petrol, motor oil, motor cars, distribution channels, politicians, newspapers and TV programmes. The pattern had already been observed in the UK, USA, Europe and Japan, across demographic subgroups and in periods ranging from one week to two years.

Between 1991 and today however, global internet connectivity, wireless mobile devices and several financial crashes have reshaped consumer choice behaviour. Advances in technology have also multiplied the volume and types of consumer data now available, which in turn helps to drive globalisation (Steenkamp et al 2003). In addition, market concentration (Morgan & Rego, 2009), saturation (Liu & Yang, 2011) and the emerging-market imperative (Chattopadhyay, Batra, & Ozsomer, 2012) have led to intensifying competition through new distribution channels, particularly hard discounters, convenience stores and on-line grocery (Campo & Breugelmans 2015), all leaving marketers no choice but to respond to the changing competitive consumer landscape (Kapferer & Bastien, 2009).

Throughout these perturbations, and perhaps because of them, loyalty has never gone out of fashion. It is still widely held that brands should build ever- stronger emotional ties with their buyers (Bohling *et al* 2006) leading to patronage behaviour that might break the constraints of Double Jeopardy. And the ubiquity of social media has now spawned strategies that aim to build customer brand engagement (Hollebeek, 2011) brand enmeshment (de Villiers, 2015) and even brand love (Batra, Ahuvia, & Bagozzi, 2012). Yet despite the best efforts of marketers, the behavioural outcomes of these effects are simply not seen as often as such authors expect given the current evidence for DJ in many categories (Sharp, 2010), whilst recent results about the long-term persistence of behavioural loyalty (Dawes *et al.,* 2015) pose further questions about its value to management as a focus for growth.

More than ever then, before investing in loyalty-building schemes it is important to understand the structure of the market and any brand performance metrics that a strategy hopes to change. If the Double Jeopardy law and its *w*(1-*b*) approximation hold across a wider range of conditions in contemporary marketing then the underlying theory becomes stronger and managers gain a robust but easily applied tool with which to develop actionable insights about competitive market structure.

*2.3 The derivation of the w(1 - b) model*

Ehrenberg and Bound (1993) noted that the *w*(1- *b*) model was initially derived not from observation, but from two assumptions of independence established by Goodhardt and Chatfield. These assumptions (Ehrenberg *et al.,* 1990, p.86) are:

1. That the buying of different brands is independent across consumers
2. Brands do not differ in how often their customers on average buy the total product category (i.e. any brand)

Their elegant algebraic proof from these assumptions bears repetition here, as it provides the higher-level theory on which the empirical generalisation rests.

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| Consider for simplicity just three brands, A, B, and C. Brand A’s buyers’ average rate of buying the product category is then (*b*A*w*A + *b*BA*w*B.A + *b*CA*w*C.A)/*b*A where *b*BA is the proportion of the population who buy both brands B and A in the analysis period, and*w*B.A is their average frequency of buying B, given that they also bought A. On assumption a) above, we can write *b*BA = *b*B*b*A and *w*B.A = *w*B.. Hence A’s buyer’s rate of buying the product category simplifies to *w*A + *b*B*w*B + *b*C*w*C, and similarly we have *w*B + *b*A*w*A + *b*C*w*C for B’s buyers rate of buying the product category. On assumption b) these two rates should be equal. Cancelling the common term *b*C*w*C therefore gives *w*A + *b*B*w*B = *w*B + *b*A*w*A. Collecting terms in A and B then gives *w*A(1- *b*A) = *w*B(1- *b*B) = a constant. This form of DJ therefore has to happen if assumptions a) and b) are true, as they approximately are.*Ehrenberg & Bound, (1993) p.184*  |

Neither the assumptions nor the proof allow for the effects of brand-level segmentation or a more loyal (hence valuable) customer base, or indeed for any loyalty-based competitive outcomes. They theoretically underpin both the *w*(1- *b*) and NBD-Dirichlet models. When these models fit, DJ is present, as many investigations of competitive market structure have continued to show (e.g. Anesbury *et al.,* 2017; Dawes *et al,* 2015; Dawes, 2016; Ehrenberg *et al,* 2004; Romaniuk & Sharp, 2016; Stocchi *et al,* 2015; Sharp *et al.,* 2012). This reveals in turn the existence of an approximately constant level of loyalty ***for the category*** that can be estimated at brand level simply from the number of buyers attracted - brand size:

 (2) *w*x(1 - *b*x) $≅$ *w*y(1 - *b*y) $≅$ *w*o

Equation (2) suggests that the average purchase frequency for a brand will be lower for a smaller penetration, and higher with greater customer numbers, but that the relationship is not linear; the full Double Jeopardy curve is an extreme J-shape (East, Wright & Colombo, 2004; Habel & Rungie, 2005). In practice market shares are often in a fairly closely clustered range and so variation in *w* is observed to be low, but if the spread in penetration values between competing brands increases in some condition (say in longer term data, or in categories with a very large leading brand) then purchase frequencies are expected to become (and in practice are) more widely divergent.

In order to apply the model, given a set of available buying metrics for a range of competing brands, the constant *wo* is estimated as the mean value of *w*(1 – *b*) across the range, and the expected purchase frequency for any brand in the category may be predicted from its actual or desired penetration, using the expression *wo* /(1 - *b*) (See Ehrenberg *et al* 1990).

In reporting the thirty-two replications conducted in this study, the paper proceeds as follows. In the next section we discuss the data used and the analysis, then address the research questions by presenting and assessing the model fittings across the variety of conditions identified. We conclude by outlining the theoretical and managerial implications of these results.

**3. Method**

*3.1. Data*

The study considered commercial panel datasets provided by Kantar Worldpanel, and collected in various countries and times over the past twenty years. The panels comprise several thousand household participants continuously recording their purchases using in-home electronic terminals, and are demographically and geographically weighted. For commercial aircraft manufacturers, sales records covering all customers were combined to create a category database.

 *3.2 Data analysis and standard buying measures*

The analysis technique required inputs of category and brand purchase occasions aggregated in set time periods. For commercial aircraft, that period was the ten years between 2005 and 2015. In CPG, proprietary software allowed the extraction of panel data at brand, variant or firm level, filtered to include only continuous reporters, thus allowing the study of cumulative buying from the short to the long-run. The standard buying measures required were calculated as follows:

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| **Category penetration (B)** | *The proportion of available customers that bought the category at least once in the specified period.* |
| **Average category purchase frequency (W)** | $$\frac{Total category purchase occasions}{B}$$ |
| **Brand penetration (*b*)** | *The proportion of available customers that bought the brand at least once in the specified period.* |
| **Average brand purchase frequency (*w*)** | $$\frac{Total brand purchase occassions}{b}$$ |
| **Brand share** | $$\frac{Total brand purchase occassions}{Total category purchase occassions}$$ |

In each replication the observed (O) purchase frequencies for each brand were compared with two theoretical measures, **Td** derived from the NBD-Dirichlet (See Ehrenberg, Uncles & Goodhardt, 2004) for a technical description of the fitting procedure) and **To** from the *w*o /(1- *b*) arithmetic. Following Ehrenberg (1982), observed and theoretical brand performance was tabulated in market share order to reveal the DJ characteristic in each condition and the arrays summarized in column averages. Model fittings were evaluated by assessing whether the Double Jeopardy relationship held within what Ehrenberg & Bound described as “the limits of scatter”.

*3.3 The limits of scatter*

Driesener, (2005), Scriven & Bound, (2004) and Wright, Sharp and Sharp (2002) suggest four tests be applied to arrays of fittings to assess this; the correlations between O and **T**, the Mean Absolute Deviation (mean |O-**T**|) and the Mean Absolute Percentage Error (mean (O-**T**)/**T**), and suggest a visual test for the presence of the characteristic DJ bias invalues of *w* between the biggest and smallest rival brands.

Wright *et al* (2002) argued that a range of tests is required since MAD gives lower errors for smaller brands and MAPE for larger brands, while correlation is sensitive both to the number of observations and, (Scriven and Bound, 2004), low variability in the array of interest. In these prior studies acceptable values for tests of **T** were established to be correlations greater than *r* =0.6, MADs of less than 0.9, MAPE’s less than 20%, and a visible DJ characteristic.

**4. Results**

*4.1 Replications in time & place: Instant Coffee, then, there, here and now*

Two replications were performed of the US instant coffee example in Ehrenberg, Goodhardt & Barwise (1990). With new data, the replications (Table 1) were expanded to the UK and Denmark after a gap of thirty three years. The main finding is that even across countries and over time, households that buy instant coffee *still* typically choose a brand about three times a year (no international loss of loyalty then, but a wide variation in numbers of buyers). In the replications the DJ relationship reflected the original data in direction and size and despite great variation in category and brand penetrations and in the brands themselves, in all three markets the predictive power of both models was good, with strong correlations between theoretical (**Td** and **To**) and observed purchase rates and low MADs and MAPEs.

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Table 1 about here

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As noted in Ehrenberg et al., (1990), modelling the DJ relationship highlights exceptions for investigation. In the US, Brand B (Sanka) showed slightly higher purchasing than expected while Brand G (Brim) had a lower frequency than its penetration suggests, which was noted as a temporary fluctuation. Khan *et al.,* (1988) defined these exceptions as niching and change of pace where a variance in purchase frequency for an individual brand exceeds 10% from its prediction. In Table 1, deviations were seen in Denmark where Brand G is niching and in the UK, where Brand E shows a change-of-pace characteristic against **Td** (-18%) but not **To** (-9%). Further investigation often reveals these exceptions to be temporary (the result of a promotion perhaps) or otherwise related to a partition in which clusters of brands share obvious functional differences with the category (e.g. decaffeinated and caffeinated coffee, adult and children’s’ breakfast cereals). The point is however, that only by knowing the main patterns can the exceptions be identified and investigated.

*4.2 Replications in time: pre- and post-online grocery shopping.*

Twenty further replications were conducted comparing buying in ten CPG categories fifteen years apart (Table 2). Both the NBD-Dirichlet and the *w0* /(1–*b*) equation gave remarkably consistent results for these 400 brands, as summarised at the base of the table. The categories include a broad range of buying with annual brand penetrations from 16% to just 1% and average purchase frequencies from ten times per year to just twice. Dirichlet output was slightly closer to observed values with better correlations and lower MADs and MAPE descriptions of scatter. It can be seen that correlations between observed and theoretical measures of *w* are lower than expected for both models. The data show some slight trends too; margarine and decaffeinated coffee have both become a little less popular, yet both fittings continued to capture the expected purchase frequencies of the brands so that buying continues to be just about normal amongst the remaining category consumers.

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Table 2 about here

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Note that the later data aggregates store and on-line purchasing, but as expected, this seems to have had little effect on the purchase frequency of the brands bought (see Dawes & Nenycz-Thiel, 2014; Anesbury *et al.,* 2016). However, some fittings stand out as exceptional. Both premium ice cream and tea bags showed extremely low correlations between observed and theoretical values of *w*. This is because Private Labels account for over half of all sales in these categories; Private Labels often have the purchase frequencies of big brands but their sales are constrained by a restricted distribution that limits penetration and leads to a niching characteristic (Dawes & Nenycz-Thiel, 2013; Uncles & Ellis, 1989). The dog food measures of scatter are also elevated because *w* values are high; further analysis would now be appropriate to confirm whether in this category buying is partitioned, perhaps between small super-premium pack sizes and larger everyday brands.

In summary, in these categories repeat-purchase loyalty appears to have changed little between 1998 and 2014, suggesting that established patterns of buying behaviour are simply being spread across more channels; fittings of both models to the observed values of *w* were comparable.

*4.3 Replications in time: cumulative and continuous buying*

A third set of replications was conducted using cumulative observations ranging from one quarter to six years of continuous buying (Table 3). The *w0* /(1–*b*) model was developed using short time periods in which customers make few purchases, so that average *w* values were hardly likely to differ much between rivals, but Ehrenberg (1988) and Khan, Kalwani & Morrison (1988) both demonstrated how the constant grows in periods up to a year. Little research has yet examined the evolution of DJ over extended purchase sequences in which loyalty strategies should clearly repay their investment. Cumulative growth in penetration and purchase frequency takes separate forms, so that in very long periods the fixed DJ relationship might eventually break down, breaching model assumptions and hence the continuing fit.

Over time, even in conditions of market share equilibrium, penetration measures rise dramatically (often doubling between a quarter and a year), growing steeply at first, then continuing to grow more slowly over years as the brand attracts its very lightest buyers for the first time. In theory (and the NBD and NBD-Dirichlet predict this) given *enough* years, any brand would reach all buyers in the market once. Penetration grows for every brand, but an important point is that bigger brands (being bigger) acquire their buyers rather faster than smaller brands and so their cumulative penetration growth curve begins to slow sooner. Cumulative purchase frequency on the other hand grows linearly with time, but again, faster for bigger brands, and slower for smaller. The effects on the DJ relationship have seldom been observed, but new types of continuous data do now make it possible to analyse longer observation periods, in which very large numbers of purchases are made.

To test the persistence of DJ in cumulative brand and category performance, both models were fitted to observations in the near-stationary UK shampoo category in the familiar short term quarter and half year periods and again to six years of continuous buying (Table 3).

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Table 3 about here

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The first point to note is that whatever the length of data aggregation, brand shares remained stable (as would be expected in a stationary market). Table 3 then shows that category penetrations doubled between six months and six years to reach almost all households, while average brand penetrations (column averages) grew five-fold, the result of continuous brand switching. Mean *w* doubled, while the range of *w* values increased across the brands, from the near parity seen in one quarter, in a spread of values that seems unfamiliar in comparison with usual management periods.

Some might take the far higher loyalty observed for the bigger brands as evidence of superior “brand strength” emerging over time. It is not. As East, Wright & Colombo (2004) explain, it is the necessary outcome of market share equilibrium; to maintain cumulative sales growth, as penetration slows purchase frequency rates must keep rising as a statistical artefact, since having already acquired more buyers, the probability of subsequent purchases in the customer base increases. This happens faster for bigger brands and more slowly for smaller, but Table 3 shows that this changing relationship remains predictable. Despite the great number of purchases observed, both models were found to be robust enough to estimate purchase frequencies in each replication and the simpler model made predictions of **To** in six years that were on average within about one quarter of a purchase.

Nevertheless, the shampoo category is highly competitive, with most brand shares in single digits, and comparatively low brand penetrations. After six years the average brand had appeared in just a quarter of all households, although the category itself had reached almost every home. Further replications of cumulative buying in categories with higher penetration are now needed to examine cumulative buying in more detail.

In response to Research Question One then, the Law of Double Jeopardy appears astonishingly robust against the ravages of time, despite the many changes time inevitably brings about on shopping habits. The oldest data here is from 1985, the next oldest from 1998, both pre-smartphones and the real advent of online grocery shopping. Between then and now new store types have emerged; brands have introduced innovative new line extensions, different pack sizes and variants to better match consumer needs and wants; new brands have been added into the repertoire and some dropped for a while; many individual households have changed size, and people have moved towns countries or continents. Nevertheless the model fittings demonstrate that the underlying assumptions of Double Jeopardy continue to hold, that they are maintained even over the long run, and that therefore behavioural loyalty for any brand remains surprisingly predictable over time.

 *4.4 Replications in non-western markets: Egypt*

The underlying theoretical assumptions of both the models suggest that consumers are experienced about categories and the range of available brands; any learning has already happened (Ehrenberg, Uncles and Goodhardt, 2004). This is less likely to be the case in growing markets, where market shares might well be non-stationary. The models are not dynamic but they are fitted to market structure in temporal slices; evolution, if it is occurring, may then be considered in a series of steps within which buying behaviour appears to remain normal (see Bennett and Graham, 2010).

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Table 4 about here

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Two replications were conducted in annual data from Egypt, a rapidly growing economy. Table 4 shows that both models nevertheless fit to annual observations and reveal DJ buying in the Egyptian chocolate confectionary category, across the country, but also in the large “Bottom of the Pyramid” (BoP) market segment (17 million people living on less than $2 a day) where the *w0* /(1 – *b*) model identified a consistent and predictable rate of sale for the local Mandolin brand and its international competitor Cadbury. Cadbury is not a newcomer, having been in the market for almost thirty years, but the analysis reveals that although share ranking is reversed in the BoP segment, both brands can attribute leading performance to their presence across the *entire* market rather than to targeting a small and wealthy niche. Mandolin performance is consistent at the market level and within the BoP, while Cadbury shows a niching characteristic in both.

*4.5 Replications in non-western markets: Russia*

Two further replications compared buying in the growing Russian economy with the established UK market. The study considered nappies and confirmed that buyers in the two markets buy brands at very similar mean rates even though the penetration measures in the data appear to be different. In Russia brand penetrations were much higher because the panel consisted only of category shoppers (and the actual category penetration was not available at the time of the analysis) whereas the UK penetration observations were on a base of all households. Both model fittings (Table 5) nevertheless gave acceptable correlations, MADs and MAPEs, and supported the response to Research Question Two that the models are robust enough to estimate buying from a range of data types and in non-western markets.

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Table 5 about here

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*4.6 Replications in new conditions: capital goods and house of brands strategies*

In response to the third research question, in a pioneering exploration of capital goods buying, the *w*/(1 – *b*) model was used to estimate purchasing records for large commercial aircraft. The manufacturers’ data reported every aircraft sold from 2005 to 2015 (about 9,000 sales in total to over 800 customers). The data included six aircraft corporate brands plus 'other'.

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Table 6 about here

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While a Dirichlet analysis was not attempted, results are clearly consistent with brand purchasing patterns found in consumer categories despite the fact that two manufacturers dominate the market and that the ten–year data aggregation led to a high variance in purchase frequencies. The analysis is presented at the corporate level (Boeing, Airbus rather than 747 or A380) and therefore considers portfolios of brands. It also describes the *number* of planes sold rather than orders made, which might include several planes and may account here for a slightly high MAPE in fittings. In Dirichlet analyses in CPG categories the standard measure is usually of choice, and disregards the volume of a purchase. Any discrepancy is normally considered to “come out in the wash” (Ehrenberg, 1988) but here in a market with fewer buyers and a product that costs $350 million (before engines) one or two more or less on an order is clearly an important consideration, a fact which should be taken into consideration when designing and considering further replications.

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Table 7 about here

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Like the Dirichlet, the simpler model appears to be flexible enough to accommodate aggregation of choices to higher and lower levels of market structure, that is, down to the product variant level, or up to the corporate level in a house of brands strategy. A further analysis is therefore presented of brands aggregated into company portfolios in the UK shampoo category (Table 7). Penetration levels for each brand portfolio are calculated as the sums of the subsidiary brands, and as with aeroplane buyers, it shows that the relationship between penetration and purchase frequency is maintained. The Dirichlet gives a close fit, but *w (1 –b)* has slightly over-predicted loyalty to the two leading portfolios and under-predicted loyalty to the smaller. Nevertheless, this replication suggests a promising approach to portfolio management in establishing the extent of category purchasing covered by the portfolio and identifying brands that might be contributing more (or less) than expected.

In summary, no boundary conditions were found across all the replications conducted and the predictive accuracy of repeat purchase loyalty from both models was found to be comparable. Systematic differences did become clear when each model's fit was graphed in a DJ line (Habel & Rungie, 2005). Figure 1 gives an example, and compares average O, **Td** and **To** values in brand rank order for twenty brands in ten CPG categories in 2014. It can be seen that that *w*(1- *b*) slightly but systematically over-predicts while the Dirichlet slightly under-predicts purchase frequenciesfor the largest brands. While this under-prediction of *w* for very large brands is well documented for the Dirichlet (Fader and Schmittlein, 1993; Pare and Dawes, 2012), leading to the view that it may be a systematic deviation, it does not seem to occur for the simpler model, which fits the largest brands rather better. At the lower end of the scale too, observed buying data is scattered both above and below its predicted rates, but the simpler model also tends to get closer to the smallest brands, under predicting loyalty in the mid range. Variances (as reported) are however acceptable, and on average not more than about a half purchase over a one year time frame.

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Figure 1 about here

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**5. Discussion**

We have reported thirty-two separate replicated extension studies of the Law of Double Jeopardy and predicted theoretical repeat purchase rates for over 500 brands. The replications described the competitive performance of these brands across varied conditions that were designed to a) extend tests for DJ to new categories, time frames and market situations, and b) to evaluate the robustness of a simple but under-reported model in comparison to the NBD-Dirichlet.

In answer to the first three Research Questions, Double Jeopardy was found in every replication, and in answer to the fourth the *w*(1- *b*) approximation performed well in predicting average brand purchase frequencies within much the same limits of scatter as the rather more complex NBD-Dirichlet. It did so merely using the penetrations of the competing brands in the period as input. This seems astonishing given the importance that many practitioners still place on building a competitive advantage from brand loyalty.

Perhaps the very simplicity of the *w*(1- *b*) calculation has made it somehow less credible or not worth a continued systematic testing regime. It is nevertheless true that its simplicity masks a complex theoretical underpinning, with two fundamental assumptions about repeat buying which remain widely empirically supported (including in further extensions here) yet are probably counter-intuitive to many. On the other hand it is the parsimony of the calculation that makes it so managerially useful in a very wide range of applications, either to test for the Double Jeopardy condition, or in support of strategic decisions, or to evaluate their outcomes.

*5.1 Practical Applications*

We now briefly list some of the many practical applications of the *w0* /(1 – *bx*) model.

*5.1.1 Brand audits*

In the categories and conditions tested here, some for the first time, the underlying competitive structure has been revealed to show that most brands are closely governed by the law-like relationship between brand penetration and purchase frequency. Since most brands are “normal” (in that they are very close to the predicted DJ line), any exceptions are easily spotted and can be investigated further much as we have done here. Further work might then reveal that a deviation is only temporary but manageable (perhaps because of an out of stock at a major customer), or it may be one of a number of known but systematic variances such as the performance of seasonal brands or Private Labels. Unusually high repeat purchase rates may equally reveal undue market influence, as Ehrenberg, Goodhardt and Barwise (1990) found in the prescribing of hypertension drugs. Using the simple model such anomalies can be easily identified for owned or for competitor brands, and then investigated further.

*5.1.2 Market audits*

Any manager thinking of entering a new country, market or category will first ask what that market is like. This type of exploration was exemplified by the results based on data from Egypt, and in the aircraft purchasing reports. In both cases, findings could be easily interpreted in the context of existing knowledge, exceptions or peculiarities identified, and actionable insight developed.

For example, it is clear that not all aeroplanes are equal; the bulk of the observed purchasing was for jet airliners, but one brand, ATR, makes only smaller propeller aircraft, and this was reflected in a purchase frequency at just half of its predicted rate. Knowing the main patterns helps to draw insight from such exceptions in the data. It must be expected that the deviation will be persistent; it highlights that a niching strategy (e.g., *specialising* in propeller aircraft), if one is being followed, cannot be a panacea to ferocious competitive in this duopolistic market, since purchase frequency for ATR planes was lower rather than higher than the expected rate. Nevertheless a great number of smaller brands are observed to show a persistent deficit loyalty and yet survive (Franke *et al.,* 2017)

In Egypt, the market is large and the economy is growing, and the analysis showed that normal patterns held. To win a substantial market share in Egypt must therefore mean attracting a substantial number of buyers at every level of the pyramid. Both leading brands, one local, one international, have developed solutions to the distribution and pricing barriers in this market in order to gain access to the entire population. The *w*(1- *b*) model shows why targeting a niche is not a share-building option.

*5.1.3 Marketing strategy and planning*

When launching new products an estimate of sales or expected market share is used to justify the marketing investment. With basic knowledge of the market or category, it is straightforward to work out the required penetration and purchase frequencies needed to generate the anticipated results. The *w*(1-*b*) model helps with this. Sales depend on both metrics, but Double Jeopardy makes that relationship predictable. Six monthly sales for nappy brands in markets as far apart as Russia and the UK appear to be about four packs per buying household, but there is some variability according to brand size. The model is therefore a useful tool to set realistic brand sales targets in any market, and for managers to understand how those targets can be achieved (i.e. largely by maintaining penetration rates in consecutive periods) before deciding on the appropriate tactics. In addition, because the model estimates the extent to which loyalty is constrained by the DJ relationship, achievable brand growth objectives can also be planned that emphasise a faster acquisition of new buyers rather than improbable levels of repeat purchase.

*5.2 Conclusions*

Our main contributions in this research were a) to use differentiated replication and extensions to show that the Law of Double Jeopardy remains robust and continues to describe repeat buying structure both over time and in some conditions not previously examined. In doing so, we have extended the boundaries of this fundamental empirical generalisation to include long-term continuous buying, capital goods, different levels of market aggregation, and the analysis of dynamic and emerging markets. Our second major contribution was to demonstrate that a simple mathematical model, *w*(1- *b*) reliably generates theoretical levels of behavioural brand loyalty that are comparable to those generated by the more complex NBD Dirichlet. This is significant since both models share some of the same operational assumptions and therefore, the simpler model may be assumed to offer similar inferences of competitive market structure (for example the relative importance of light buyers, and the predictable patterns of customer sharing between bigger and smaller rivals) even when those measures have not been calculated.

In this article we have answered the call for more replication research in order to develop or strengthen empirical generalisations. Forty years ago the American Marketing Association set up a taskforce to develop and disseminate marketing knowledge, and empirical generalisations continue to surface on the Market Science Institute’s list of priorities. Recently Uncles and Kwok (2013) pointed out that replications are still far from the norm in business research, which may still have a long way to go in adopting scientific principles.

The idea that any research should be replicable demands that the research is first conceptualized to be replicated. Even so, articles commonly lack the basic information that would allow an independent researcher to replicate the study (e.g., sample sizes and characteristics, survey instruments, software and algorithms, descriptive statistics, or shared datasets). To be useful to practitioners, the more straightforward the techniques and the fewer the data inputs required, the better.

The limitations of this study help define potential avenues for future research. As a first pass at market analysis, brand loyalty is so easily estimated from this simple model that it deserves further systematic testing. Both *w*(1-*b*) and the NBD-Dirichlet are “zero-order” and assume every purchase to be independent of the previous one. Neither model can take into consideration covariates (e.g. household/consumer characteristics) that may influence purchase behaviour. More sophisticated models (such as the Pareto/NBD model with explanatory variables) could be used to obtain a better understanding of the causes for differences in brand purchase rates (Fader, Hardie and Jerath, 2007; Rungie, Uncles and Laurent, 2013) although at the moment this still remains at the expense of parsimony.

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**Table 1. Instant Coffee Buying Measures**

|  |  |  |  |
| --- | --- | --- | --- |
|   | **USA Annual Data** | **Denmark, Annual Data** | **UK, Annual Data** |
| **Brands** | *MRCA, USA, 1985* | *Kantar DK, 2010* | *Kantar UK, 2014* |
| **in Rank** | *b* | **Avg. Purchase Freq.** | ***b*** | **Avg. Purchase Freq.** | ***b*** | **Avg. Purchase Freq.** |
| **Order** |   | Obs. | Dir. | *wo* |   | Obs. | Dir. | *wo* |   | Obs. | Dir. | *wo* |
|   | *%* |   |   | (1 - *b*) | *%* |   |   | (1 - *b*) | *%* |   |   | (1 - *b*) |
|   |   | O | **Td** | **To** |  | O | **Td** | **To** |  | O | **Td** | **To** |
| Category  | - | - |  |  | 31 | 4.6 |  |  | 77 | 4.9 |  |  |
|   |   |   |   |   |   |   |   |   |   |   |   |   |
| Brand A | 24 | 3.6 | **3.2** | **3.1** | 14 | 3.0 | **3.0** | **2.9** | 45 | 3.5 | **3.4** | **4.2** |
| Brand B | 21 | 3.3 | **3.0** | **2.9** | 11 | 3.3 | **2.9** | **2.8** | 19 | 2.5 | **2.8** | **2.9** |
| Brand C | 22 | 2.8 | **2.9** | **3.0** | 9 | 2.3 | **2.7** | **2.8** | 10 | 2.7 | **2.7** | **2.6** |
| Brand D | 22 | 2.6 | **2.9** | **3.0** | 5 | 2.6 | **2.5** | **2.7** | 4 | 2.9 | **2.6** | **2.4** |
| Brand E | 18 | 2.7 | **2.9** | **2.8** | 5 | 2.4 | **2.5** | **2.7** | 4 | 2.2 | **2.6** | **2.4** |
| Brand F  | 13 | 2.9 | **2.8** | **2.7** | 5 | 2.1 | **2.5** | **2.7** | 3 | 2.7 | **2.6** | **2.4** |
| Brand G | 9 | 2.0 | **2.6** | **2.5** | 2 | 3.4 | **2.4** | **2.6** | 1 | 2.4 | **2.6** | **2.3** |
| Brand H | 6 | 2.6 | **2.6** | **2.5** | - | -  |  - |  - | 1 | 2.2 | **2.6** | **2.3** |
|   |   |   |   |   |   |  |  |  |   |   |  |   |
| **Average** | 17 | 2.8 | **2.9** | **2.8** | 7 | 2.7  | **2.7** | **2.6** | 11 | 2.6 | **2.8** | **2.7** |
|   |   |   |   |   |   |   |  |  |   |  |  |  |
| Correlation |   |   | *0.87* | *0.70* |  |   | *0.84* | *0.73* |  |   | *0.84* | *0.83* |
| MAD |   |   | 0.3 | 0.3 |   |  | 0.3 | 0.4 |   |   | 0.2 | 0.3 |
| MAPE % |   |   | 9 | 11 |   |  | 12 | 14 |   |   | 8 | 10 |
| *In Denmark, brand G is a strongly niching exception . Correlations shown exclude this outlier. Data are rounded.* |

 **Table 2. Replications in Annual Data, 1998 and 2014**

|  |  |  |  |
| --- | --- | --- | --- |
| Categories(Top 20 brands in each) | **Av Brand Observed** | **Dirichlet fittings** | **wo/(1-b) fittings** |
|   | *b* | *w* | **Td** | *r =* | MAD | MAPE% | **T**o | *r =* | MAD | MAPE% |
| **UK 1998** |   |   |   |   |   |   |   |   |   |   |
|  Margarine | 16 | **4.8** | **4.8** | 0.7 | 0.6 | 12 | **4.8** | 0.6 | 0.7 | 14 |
|  Wet Ambient Soup | 11 | **5.0** | **5.0** | 0.6 | 0.8 | 17 | **5.2** | 0.6 | 1.0 | 20 |
|  Tea Bags | 10 | **4.5** | **4.1** | 0.1 | 0.9 | 22 | **4.5** | 0.0 | 0.9 | 21 |
|  Toothpaste | 10 | **2.7** | **2.8** | 0.7 | 0.3 | 10 | **2.8** | 0.6 | 0.3 | 12 |
|  Butter | 8 | **4.3** | **4.5** | 0.7 | 1.0 | 22 | **4.2** | 0.6 | 1.0 | 24 |
|  Body Sprays & Deos | 8 | **2.1** | **2.0** | 0.6 | 0.3 | 14 | **2.1** | 0.5 | 0.3 | 15 |
|  Dog Food | 5 | **9.9** | **9.4** | 0.6 | 2.8 | 30 | **9.9** | 0.3 | 3.3 | 33 |
|  Premium Ice Cream | 4 | **2.4** | **2.2** | 0.1 | 0.5 | 23 | **2.4** | 0.0 | 0.6 | 24 |
|  Porridge /Instant  | 4 | **2.3** | **2.4** | 0.5 | 0.4 | 15 | **2.4** | 0.4 | 0 | 16 |
|  Decaffeinated Coffee | 2 | **2.6** | **2.8** | 0.4 | 0.6 | 22 | **2.6** | 0.3 | 0.6 | 24 |
| **UK 2014** |   |   |   |   |   |   |   |   |   |   |
|  Margarine | 14 | **3.8** | **3.8** | 0.6 | 0.5 | 15 | **3.8** | 0.6 | 0.6 | 17 |
|  Wet Ambient Soup | 10 | **4.0** | **4.1** | 0.7 | 0.8 | 21 | **4.0** | 0.6 | 0.9 | 22 |
|  Body Sprays & Deos | 9 | **2.3** | **2.2** | 0.6 | 0.3 | 12 | **2.2** | 0.5 | 0.3 | 13 |
|  Toothpaste | 9 | **2.2** | **2.3** | 0.7 | 0.3 | 15 | **2.3** | 0.7 | 0.4 | 16 |
|  Butter | 9 | **3.6** | **3.9** | 0.8 | 0.7 | 19 | **3.6** | 0.7 | 0.7 | 20 |
|  Tea Bags | 9 | **3.2** | **3.0** | 0.3 | 0.4 | 14 | **3.2** | 0.2 | 0.5 | 16 |
|  Premium Ice Cream | 6 | **2.3** | **2.1** | 0.1 | 0.4 | 18 | **2.3** | 0.0 | 0.4 | 18 |
|  Porridge /Instant  | 5 | **2.4** | **2.4** | 0.5 | 0.3 | 10 | **2.4** | 0.4 | 0.3 | 11 |
|  Dog Food | 4 | **12** | **11** | 0.7 | 3.0 | 29 | **12** | 0.3 | 4.0 | 31 |
|  Decaffeinated Coffee | 1 | **3.3** | **3.3** | 1.0 | 0.4 | 16 | **0.5** | 0.2 | 0.4 | 17 |
|   |   |   |   |   |   |   |   |   |   |   |
| **Average**  | **8** | **3.9** | **3.9** | **0.5** | **0.8** | **18** | **3.9** | **0.4** | **0.9** | **19** |
| *Source; Kantar n = 15,000. Data are rounded.* |

**Table 3. Cumulative continuous buying: UK Shampoo brands**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | **One Quarter** | **Six Months** | **Six Years** |
| **Brands in** |  |  | **Avg. Purchase Freq.** |  | **Avg. Purchase Freq.** |  | **Avg. Purchase Freq.** |
| **Rank Order** | Share | *b* | Obs. | Dir. | *wo* | *b* | Obs. | Dir. | *wo* | *b* | Obs. | Dir. | *wo* |
|  | *%* | *%* |  |  | (1 - *b*) |  |  |  | (1 - *b*) |  |  |  | (1 - *b*) |
|  |  |  | O | **Td** | **To** |  | O | **Td** | **To** |  | O | **Td** | **To** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Category** |  | **40** | **1.8** |  |  | **55** | **2.6** |  |  | **92** | **19** |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Pantene | 10 | 5 | 1.4 | **1.3** | **1.3** | 8 | 1.8 | **1.6** | **1.6** | 35 | 5.0 | **4.4** | **4.2** |
| Head & Shoulders | 9 | 5 | 1.3 | **1.3** | **1.3** | 8 | 1.6 | **1.6** | **1.6** | 29 | 5.1 | **4.2** | **3.9** |
| L’Oreal Elvive | 6 | 4 | 1.3 | **1.3** | **1.3** | 6 | 1.5 | **1.5** | **1.6** | 31 | 3.5 | **3.9** | **4.0** |
| Herbal Essences | 6 | 3 | 1.3 | **1.3** | **1.3** | 5 | 1.5 | **1.5** | **1.6** | 27 | 3.6 | **3.9** | **3.7** |
| Organics | 5 | 3 | 1.4 | **1.3** | **1.3** | 4 | 1.6 | **1.5** | **1.5** | 24 | 3.5 | **3.8** | **3.6** |
| Fructis | 4 | 2 | 1.3 | **1.3** | **1.3** | 4 | 1.5 | **1.5** | **1.5** | 21 | 3.1 | **3.6** | **3.5** |
| Timotei | 4 | 2 | 1.3 | **1.3** | **1.3** | 3 | 1.5 | **1.5** | **1.5** | 20 | 2.9 | **3.6** | **3.4** |
| Vosene | 3 | 2 | 1.3 | **1.3** | **1.3** | 3 | 1.5 | **1.5** | **1.5** | 16 | 3.0 | **3.5** | **3.2** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Average** | **6** | **3** | **1.3** | **1.3** | **1.3** | **5** | **1.6** | **1.5** | **1.6** | **25** | **3.7** | **3.9** | **3.7** |
|   |   |   |   |   |   |   |   |  |   |   |   |   |   |
| Correlation |   |   |   | 0.78 | 0.78 |   |   | 0.81 | 0.70 |   |   | 0.96 | 0.80 |
| MAD |   |   |   | 0 | 0 |   |   | 0.1 | 0.1 |   |   | 0.5 | 0.2 |
| MAPE (%) |   |   |   | 3 | 3 |   |   | 3 | 6 |   |   | 13 | 12 |

*Kantar Worldpanel: continuous buyers 1999-2005 (a subset of c. 4,000 households). Data are rounded.*

**Table 4. Buying measures in the Chocolate Confectionary category in Egypt (2015)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|   |   | **Total Market** |  | **Bottom of the Pyramid** |
| Brands | Share | *b* | *w* | Dir | *wo* |  | *b* | *w* | *wo* |
|   | % | % |  |   | (1 - *b*) |   | % |   | (1 - *b*) |
|   |   |   | O | **T** | **T** |   |   | O | **T** |
| **Category** |   | 68 | 6.8 |   |   |   | 64 | 4.9 |   |
|   |   |   |   |   |   |   |   |   |   |
|  Cadbury | 33 | 36 | 4.2 | **3.6** | **3.1** |  | 24 | 3.0 | **2.2** |
|  Other | 20 | 27 | 3.3 | **3.0** | **2.7** |  | 32 | 3.3 | **2.5** |
|  Mandolin | 18 | 30 | 2.7 | **2.9** | **2.8** |  | 29 | 2.7 | **2.4** |
|  Galaxy | 13 | 24 | 2.6 | **2.7** | **2.6** |  | 12 | 2.4 | **1.9** |
|  Kit Kat | 4 | 9 | 2.3 | **2.4** | **2.2** |  | 2 | 1.4 | **1.7** |
|  Snickers | 3 | 5 | 2.5 | **2.3** | **2.1** |  | 1 | 1.0 | **1.7** |
|  Moro | 3 | 6 | 2.1 | **2.3** | **2.1** |  | 4 | 1.3 | **1.8** |
|  Bubbly | 2 | 6 | 1.7 | **2.3** | **2.1** |  | 4 | 2.0 | **1.8** |
|  Gersy | 2 | 6 | 1.6 | **2.3** | **2.1** |  | 5 | 1.5 | **1.8** |
|  Twix | 1 | 3 | 2.0 | **2.3** | **2.1** |  | 1 | 1.0 | **1.7** |
|   |   |   |   |   |   |   |   |   |   |
| **Average** | **10** | **15** | **2.5** | **2.6** | **2.4** |  | **11** | **2.0** | **2.0** |
|   |   |   |   |   |   |   |   |   |   |
| Correl. *r =* |   |   |   | 0.94 | 0.88 |   |   |   | 0.92 |
| MAD |   |   |   | 0.4 | 0.4 |   |   |   | 0.5 |
| MAPE %  |   |   |   | 19 | 17 |   |   |   | 26 |

*Source, Kantar Egypt, n = 3265. BoP missing data are brands with < 0.1% penetration. All data rounded.*

**Table 5. Nappies in the UK and Russia**

|  |  |  |  |
| --- | --- | --- | --- |
|   | **United Kingdom** |  | **Russia** |
|  | *6 Months, 2007* |  | *6 Months, 2012* |
| **Brands in** **rank order** | *b* | *w* | Dir |  *wo*  |  | *b* | *w* | Dir | wo |
|   | % |  |   | (1 - *b*) |  | % |  |   | (1 - b) |
|   |   | O | **Td** | **To** |  |  | O | **Td** | **To** |
|   |   |   |   |   |  |   |   |   |   |
|  Brand A | 11 | 6.2 | **6.0** | 4.5 |  | 69 | 7.0 | **6.9** | **8.7** |
|  Brand B | 9 | 4.6 | **5.0** | 4.4 |  | 49 | 5.0 | **4.9** | **5.3** |
|  Brand C | 4 | 6.0 | **4.3** | 4.2 |  | 31 | 4.4 | **4.2** | **3.9** |
|  Brand D | 3 | 3.2 | **3.7** | 4.1 |  | 16 | 2.3 | **3.5** | **3.2** |
|  Brand E | 1 | 4.3 | **3.5** | 4.0 |  | 11 | 3.2 | **3.5** | **3.0** |
|  Brand F | 1 | 3.8 | **3.5** | 4.0 |  | 9 | 3.4 | **3.5** | **3.0** |
|  Brand G | 1 | 3.3 | **3.5** | 4.0 |  | 8 | 2.9 | **3.4** | **2.9** |
|  Brand H | 1 | 3.2 | **3.5** | 4.0 |  | 3 | 3.0 | **3.3** | **2.8** |
|  Brand I | 1 | 2.6 | **3.5** | 4.0 |  | 2 | 3.6 | **3.3** | **2.8** |
|  |  |  |  |  |  |   |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| **Average** | 3 | 4.1 | **3.9** | **4.2** |  | 22 | 3.9 | **4.1** | **4.0** |
|   |   |   |   |   |  |   |   |  |  |
|  Correlation *r =* |   |   | 0.79 | 0.72 |  |   |   | 0.95 | 0.94 |
|  MAD |   |   | 0.4 | 0.9 |  |   |   | 0.3 | 0.6 |
|  MAPE % |   |   | 22 | 21 |  |   |   | 10 | 14 |
| *Sources: Kantar Worldpanel (n=15000) & proprietary data.* *All data rounded* |
| *Brand Descriptors:* | ***UK:*** *C to I are all PLs & E is Hard Discount* |  ***Russia:*** *D is“Other” and I is PL* |

**Table 6. Industrial Brand Loyalty (2005-2015)**

|  |  |  |  |
| --- | --- | --- | --- |
|   |  |  | **Av. Purchase Freq.** |
|  Brands | Share |  *b* | Obs. | *wo* |
|   | % | % |   | (1 - *b*) |
|   |   |   | O | **To** |
|   |   |   |   |   |
|  Boeing | 45 | 73 | 10.2 | **9.3** |
|  Airbus | 44 | 69 | 9.5 | **8.1** |
|  Canadair | 5 | 17 | 4.4 | **3.0** |
|  Embraer | 4 | 16 | 3.4 | **3.0** |
|  Other | 2 | 14 | 2.4 | **2.9** |
|  ATR | 1 | 7 | 1.1 | **2.7** |
|  Sukhoi |  < 1 | 2 | 2.0 | **2.6** |
|   |   |   |   |  |
| **Average** | 17  | 28 | **4.7** | **4.5** |
|  |  |  |  |  |
| Correlation *r =* |   |   |   | 0.97 |
| MAD |   |   |   | 0.9 |
| MAPE % |   |   |   | 27 |
|   |   |   |   |   |
| *ATR prop planes show a change of pace characteristic. Data are rounded.*  |

**Table 7. Loyalty Effects in House of Brands Strategies UK Detergent 2014**

|  |  |  |  |
| --- | --- | --- | --- |
| **Brand Portfolio Owner** |   |  | **Avg. Purchase Freq.** |
| Share | *b* | *w* | Dir | *wo* |
| % | % |  |   | (1 - *b*) |
|  |  |  | O | **Td** | **To** |
|  |  |  |  |  |  |
| Category |  | **91** | **6.4** |  |  |
|  |  |  |  |  |  |
|  P&G | 42 | 50 | 3.6 | **3.6** | **4.2** |
|  Unilever | 36 | 46 | 3.4 | **3.5** | **3.9** |
|  Tesco | 8 | 13 | 2.9 | **2.9** | **2.4** |
|  ASDA | 5 | 9 | 2.7 | **2.7** | **2.3** |
|  Morrison | 4 | 6 | 2.7 | **2.6** | **2.2** |
|  Sainsbury | 3 | 6 | 2.4 | **2.6** | **2.2** |
|  Lornameade | 1 | 1 | 1.7 | **2.5** | **2.1** |
|  Ecover | 1 | 1 | 2.3 | **2.6** | **2.1** |
|  Reckitt Benckiser | < 1 | 1 | 1.6 | **2.5** | **2.1** |
|  |  |  |  |  |  |
| Average |  | **15** | **2.6** | **2.8** | **2.6** |
| Correlation *r* =  |  |  |  | 0.88 | 0.82 |
| MAD |  |  |  | 0.3 | 0.4 |
| MAPE% |  |  |  | 10 | 16 |

*Source Kantar Worldpanel Annual data, 2014, n = 15,000. Data are rounded.*

**Figure 1. A comparison of model fit across 10 CPG categories**