**Do High Street Fashion Brands All Share the Same Types of Customers?**

**Business in a Dynamic World**

**Cyprus 2016**

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***Abstract***

It is widely thought that different brands appeal to different types of consumers and therefore countless segmentation studies are carried out. In practice however, little is known about who the customers for most brands actually are. Now, after a decade of research in FMCG categories has shown that in general the consumer profiles in developed competitive market categories differ little between brands, this study extends this research to examine consumer profiles in the high street fashion industry to see whether there are notable differences between brands in terms of the customers who buy them. Using Kantar Fashiontrack data (n=15,000) we compared the user profiles of fashion brands in the UK along demographic and psychographic dimensions. The data were categorized as ‘retail brands’ and we concentrate on the most popular category of retailing, women’s outerwear, purchased by women for themselves.

The results are that the customers of most brands are little different from the customers of other brands at the high street retailer level. However, some brands do attain a level of customer differentiation, particularly those that differentiated by age. The brands that achieve this type of segmentation are those that are part of a brand portfolio owned by a company that uses individual brands to target different user groups.

The key implication for marketing practitioners is that market segmentation using consumer characteristics will unnecessarily limit the vast potential that markets offer. Most brands would be better off with strategies that are not too narrowly focused, but that emphasize reaching as many category buyers as possible.

**Keywords: consumer profiles, segmentation, empirical generalisations.**

**1. Introduction**

Empirical generalisations or benchmarks are a form of marketing knowledge that arise from experiments or observations across a range of conditions resulting in a pattern or regularity that repeats over different circumstances and that can be described simply by mathematical, graphic or symbolic methods (Bass, 1995). The emphasis on patterns or regularities over differing circumstances is critical to developing fundamental knowledge of marketing and practical implications. A key use of rules or norms is to provide benchmarks to indicate in which conditions, regularities apply and under which conditions those regularities might not be applicable (Uncles & Wright, 2004).

***Empirical generalizations in consumer profiles***

This approach has identified that consumer profiles are homogenous across brands in a wide range of product categories and countries (e.g. Hammond, Ehrenberg, & Goodhardt, 1996; Kennedy & Ehrenberg, 2001a; Kennedy, Ehrenberg, & Long, 2000). These consistent findings show that user profiles of brands rarely differ significantly on demographic, psychographic or brand attitude variables. The implication is that brands should try to develop broad appeal across their category because marketing strategies aimed at a limited number of consumers or narrow segments unnecessarily restrict the potential customers for a brand.

Although few meaningful differences in consumer profiles are found in practice, segmentation followed by targeted marketing continues to be promoted in text books (Kotler, Brown, Burton, Deans, & Armstrong, 2010), and by a sophisticated research industry that promotes segmentation and targeting techniques as a means of achieving differential advantage (Foedemayr & Diamantopoulos, 2008). Highly targeted marketing efforts are the norm for many marketing practitioners (Franklin, 2012; O’Regan, Ashok, Maksimova & Reshetin, 2011). This is partly because targeting is conceptually appealing to managers whose marketing resources are too limited to try to address all potential customers in the marketplace. It is also true that having a target market in mind can be useful for developing creative communications strategies and also possibly for product design reasons.

**2. The body of knowledge**

Customer switching between competitive brands has been studied repeatedly over the years and the accumulated evidence is that in most categories, brands share their customers. While there are functional differences between brands in some areas—convertible sports cars are different to family estate cars—leading to some functionally-based differentiation, for the most part brands compete as if they were look-alikes. In addition, competition tends to diminish the functional differences between brands over time. There has been less work on differences in brand performance between different types of buyers but the analysis that does exist, spanning dozens of categories, usually finds that the users of competing brands have similar demographic and psychographic profiles (Kennedy, Ehrenberg and Long, 2000; Fennell, Allenby, Yang and Edwards 2003). Thus, the evidence suggests that measures of brand performance in consumer markets are generally fairly evenly spread across all customers, with large brands scoring better across all demographic or psychographic measures, and smaller brands scoring lower. This is an example of the well-known double jeopardy phenomenon—a statistical selection effect that generates the pattern favoring large brands on all brand performance metrics.

***Are there exceptions?***

Successful marketing careers have been built on doing the unexpected—a brand manager who actually manages to grow a brand’s market share, for example. Perhaps there might be other exceptions to the general findings about customer sharing as well, for example there might be categories that cater to and promote style, self-expression and individuality, where the general rules governing the patterns and structure in buying behavior and brand performance might bend a little. There may be categories where brands are more clearly differentiated and therefore do not compete as near look-alikes. An obvious candidate that might fulfill these conditions is women’s fashion.

***Fashion***

Breward (2003) describes fashion as an important conduit for the expression of social identity, political ideas and aesthetic taste. Perna (1987) deﬁnes fashion as “an expression of the times,” while Polhemus and Procter (1978) point out that the term ‘fashion’ ‘is often used as a synonym for “adornment”, “style” and “dress”.’ Coco Chanel made this point early in the 20th century saying, ‘Fashion does not exist unless it goes down into the streets. The fashion that remains in the salons has no more signiﬁcance than a costume ball’, (Charles-Roux, 1981).

For many individuals, fashion and clothing are communication tools to express personally held values. This idea was developed by McCraken and Roth (1989) who held that ‘the knowledge of a code (fashion) may have more uneven distribution for products than it does for language.’ The term ‘ high-fashion brand” refers to brands that hold considerable intangible value and have durable positive brand images at the forefront of design, quality, and status, ([Juggessur](http://search.proquest.com/indexinglinkhandler/sng/au/Juggessur,+Joshie/$N?accountid=14730) and [Cohen](http://search.proquest.com/indexinglinkhandler/sng/au/Cohen,+Geraldine/$N?accountid=14730), 2009). Fashion therefore goes hand in hand with branding, and according to Moore, (1995), high-fashion brands trade on the theory of ‘lifestyle branding,’ that stresses the images, values and elite connotations that a brand reflects to those of an aspirational consumer segment.

***Fashion Industry Size and trends***

The global retail industry has seen steady growth over the last few years and is estimated to reach $1.4 trillion by 2016 (Reportlinker, Fashion Industry, 2015). The growth of the industry also embodies dynamic changes such as the addition of new channels of distribution, resource shortages, demographic changes, new technologies, and shifts in the global economy that impact both retailers and their customers ([Pookulangara](http://www.sciencedirect.com/science/article/pii/S0969698912001506), [Shephard](http://www.sciencedirect.com/science/article/pii/S0969698912001506), 2013).

The UK fashion retail sector is characterized by high levels of concentration and domination by large multiple retailers, producing a highly competitive market, (Hines and Bruce, 2001; Jones, 2002) that has evolved in recent years, transitioning from a primarily push-based system, where designers dictated trends, to a pull system where retailers respond to consumer demands (Barnes and, Lea-Greenwood, 2010; Sull, Turconi, 2008).

Womenswear is the largest and highest profile part of the clothing industry and accounts for two thirds of the value of the adult outerwear market, reflecting women’s affinity for fashion and enjoyment of the clothes shopping experience. This enjoyment is more pronounced in some countries; in France, women’s wear makes up 25% of the market, while in the United Kingdom it constitutes just under 60% (Mintel, Global Market Navigator, 2014).

Almost six in ten (57%) British women list clothing, shoes and jewelry as spending priorities, making this their main area of discretionary spending. Young fashion-oriented women continue to underpin the performance of the market. In 2015 the UK clothing market had robust sales of £39 billion, accounting for about 5% of total UK consumer spending, (IBIS, Retailing Market Research Report 2015).

***Fashion Consumers***

Based on observations of the history of high street fashion brands for women, there are decided trends in the rising and falling popularity of brands, and so this category might represent an exception to the general rules of consumer behavior where there is great stability in the popularity and market shares of most brands. This study therefore examines the evidence available in the form of consumer purchase records from Kantar’s FashionTrak panel in the UK, to determine if women’s outerwear represents a different kind of market, where established empirical generalizations do not hold. The study examines the brand user profiles of brands in the womens’ outerwear category with special emphasis on demographic groupings. If the results are that fashion brands share their customers unevenly then we might conclude that there is user based segmentation and that would be a notable discovery. Alternatively, we may conclude that despite their best efforts, even very distinctive or iconic brands have predictable performance metrics that conform to the established laws of marketing.

***Theoretical Contribution***

Our key research question is about whether women’s fashion is a market where brands perform differently to those in other better-studied markets. If the analysis shows that they do, then this would be a signal that fashion, or the marketing interventions that drive the popularity of fashion brands, function in ways that have not been documented in competitive markets before. To discover underlying category structure and brand performance measures that are markedly different than found in previous research would be a remarkable result. It would set a precedent, and also call for further research.

**3. Method and Data Analysis**

In keeping with an Empirical Generalizations approach to marketing science, this study uses a large (n=15,000) data set covering buying behavior in the fashionable clothing category for one year. Consumer participants in the panel continuously recorded all their category purchases using electronic terminals with bar-code readers that they kept at home. The panel is weighted to accurately represent the UK population in terms of demographics and geographic distribution. It is a reliable and validated data source for a study of this type. Initially, data was extracted for the ten largest women’s outerwear brands, plus a sample of ten middle sized and ten smaller brands. This was a necessary step because of the large number of (mostly small) brands in the category. The market share figures here cover the top 80% of the market, with the remaining 20% being made up of dozens of smaller brands.

The first step in analysis is to calculate descriptive statistics such as averages, means and mean absolute deviations (MAD) (Barwise, 1995; A.S.C. Ehrenberg, 1990). This study uses the analytical framework developed for the creation and comparison of user profiles existing for developed markets (Hammond, et al., 1996; Kennedy & Ehrenberg, 2001a; Kennedy, et al., 2000; M. Uncles, et al., 2012). Variables available for analysis include gender, age, region, education, income and marital status.

The model used here was developed by Andrew Ehrenberg and Gerald Goodhardt to describe the behavior of consumers in competitive markets. It established that how often people buy a product, and the brands or products that they buy is largely habitual, with individual behavior aggregating to measures of brand performance that follow regular law-like patterns (Ehrenberg, Uncles & Goodhardt, 2004). Their approach used the well-known NBD-Dirichlet model of purchase incidence and brand choice in established competitive markets and over time showed that most markets behave in a predictable ‘Dirichlet’ manner. This led to a number of remarkable conclusions:

* Loyalty (the propensity to purchase) at the individual consumer level has multiple causes. However, it produces a common effect at the brand level, which is captured by many different measures,
* Competing brands differ little in the levels of loyalty they enjoy,
* Consumer loyalty is spread across a number of brands, some of which are bought more often than others, but all are bought more or less loyally

The NBD-Dirichlet (Goodhardt *et al.,* 1984) is a stochastic model of choice probability distributions for stationary, non-partitioned categories. To fit the model for a chosen period of time requires a calculation of the proportion of the total population that buy the category and the average number of purchases of the product category for those who purchase it. At the brand level, the inputs are the proportion of the population buying each brand and the average number of purchases of the brand by those who buy it. These data are readily available from purchase panels.

The data for this study were from Kantar’s Fashiontrak and were analyzed using proprietary software called Powerview. The program produces a number of brand performance measures such as:

1. Penetration of purchasers (percentage buying the brand at all)
2. Percentage buying the brand once and five times or more in the period
3. Average number of purchases of the brand per buyer of the brand
4. Share of category requirements
5. Percentage of sole buyers (who only buy one brand in the category)
6. Purchase rate of sole buyers

Other brand performance measures are available from detailed analysis, but are not included here as our main task is to establish whether fashion brands display the main measures similarly to those in other consumer goods categories. Table 1 is a compilation of brand performance measures (BPMs) drawn from the database of fashion shoppers. The data is from women who shopped for themselves (not for other family members or for gifts) and bought women’s outerwear at high street shops (not online purchases) during the year up to March 2012. The data have been organized by brand size, from largest to smallest. This is a standard procedure that makes it much easier to spot patterns in the data. Thus New Look is the largest brand in the market with 20% market share, followed by Other (a composite of many small brands) at 19%, Next with 15% and so on. The second column displays brand penetration—the percentage of all fashion buyers who bought each brand. The observed level of penetration (o) declines steadily with market share, as does the theoretical level (t). In fitting the model, the theoretical values are derived from the category inputs and are included here as indicators of goodness of fit.

In the ‘Purchases” section, it can be seen that on average women made 8.9 purchases per year of outerwear. Of these, the fourth column shows that customers of New Look made on average 4.4 purchases of that brand, Customers of Other, made 3.2 purchases and so on down the column. Note that the figures decline as one reads down the column, as did the figures for market penetration, both of which illustrate the well known double jeopardy phenomenon in which larger brands both have more customers, and those customers tend to be more loyal—here indicated by a higher purchasing rate. The obverse of this is seen in the next bracket of figures (Percent Buying once, or 5+ times) which shows that the percentage of once-only buyers rises as the brands get smaller, while the percentage of buyers making five or more purchases is higher for the larger brands at the top of the table.

Table 1. Example of the analysis

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Observed (O) and Theoretical (T) Performance Measures | | | | | | | | | | | | | | | | | | | | | | | | |
|  | Market | Penetration | | Purchase | | % Buying | | | | Category | | | | 100% Loyal | | | | | | | | | | | | |
| Range | Share | % | | per buyer | | Once | | 5+ | | SCR (%) | | | | Penetration | | | | | | Av Purchase | | | |
|  | % |  | |  | |  | |  | |  | | | |  | | | | | |  | | | |
|  |  | O | **T** | O | **T** | O | **T** | O | **T** | O | **T** | | | O | | **T** | | | O | | | **T** | | |
|  |  |  |  |  |  |  |  |  |  |  |  | | |  | |  | | |  | | |  | | |
| Total | 100 | 36 |  | 8.9 |  |  |  |  |  |  |  | | |  | |  | | |  | | |  | | |
|  |  |  |  |  |  |  |  |  |  |  |  | | |  | |  | | |  | | |  | | |
| New Look | 20 | 15 | **17** | 4.4 | **3.7** | 42 | **43** | 15 | **22** | 33 | **28** | | | 12 | | **14** | | | 3.4 | | | **1.5** | | |
| Other | 19 | 19 | **17** | 3.2 | **3.6** | 50 | **43** | 11 | **22** | 28 | **27** | | | 21 | | **13** | | | 2.8 | | | **1.5** | | |
| Next | 15 | 14 | **14** | 3.5 | **3.4** | 50 | **45** | 11 | **20** | 32 | **25** | | | 18 | | **12** | | | 3.2 | | | **1.4** | | |
| Hennes/H&M | 11 | 9 | **12** | 4.0 | **3.2** | 47 | **48** | 13 | **18** | 26 | **22** | | | 7 | | **11** | | | 1.8 | | | **1.4** | | |
| Dorothy Perkins | 9 | 9 | **9** | 3.0 | **3.0** | 56 | **50** | 7 | **16** | 21 | **20** | | | 9 | | **10** | | | 2.7 | | | **1.3** | | |
| Top Shop | 7 | 5 | **8** | 4.1 | **2.9** | 45 | **51** | 19 | **15** | 22 | **19** | | | 4 | | **10** | | | 1.8 | | | **1.3** | | |
| River Island | 4 | 5 | **5** | 3.1 | **2.7** | 53 | **53** | 9 | **14** | 16 | **18** | | | 2 | | **9** | | | 1.3 | | | **1.3** | | |
| Evans/Evans Col. | 3 | 3 | **4** | 3.9 | **2.7** | 52 | **54** | 11 | **13** | 49 | **17** | | | 37 | | **9** | | | 4.3 | | | **1.3** | | |
| Mackays/M&Co | 3 | 3 | **3** | 3.1 | **2.6** | 62 | **55** | 10 | **13** | 33 | **17** | | | 21 | | **9** | | | 2.6 | | | **1.3** | | |
| Gap | 2 | 2 | **2** | 2.8 | **2.6** | 68 | **55** | 5 | **13** | 22 | **16** | | | 5 | | **8** | | | 1.8 | | | **1.3** | | |
| Monsoon | 2 | 3 | **2** | 2.0 | **2.6** | 72 | **55** | 3 | **13** | 18 | **16** | | | 10 | | **8** | | | 1.9 | | | **1.3** | | |
| Miss Selfridge | 2 | 3 | **2** | 2.3 | **2.6** | 58 | **55** | 4 | **13** | 10 | **16** | | | 4 | | **8** | | | 1.2 | | | **1.3** | | |
| Zara | 2 | 3 | **2** | 2.2 | **2.6** | 69 | **55** | 4 | **13** | 12 | **16** | | | 4 | | **8** | | | 1.2 | | | **1.3** | | |
| Wallis | 2 | 3 | **2** | 2.0 | **2.6** | 68 | **56** | 4 | **13** | 20 | **16** | | | 8 | | **8** | | | 2.0 | | | **1.3** | | |
|  |  |  |  |  |  |  |  |  |  |  |  | | |  | |  | | |  | | |  | | |
| Average | 7 | 7 | **7** | 3.1 | **2.9** | 57 | **51** | 9 | **16** | 24 | **20** | | | 11 | | **10** | | | 2.3 | | | **1.3** | | |
| MAD |  | 1 | | 0.5 | | 7 | | 7 | | 7 | | | | 6 | | | | 1.0 | | | | | |
| Correlation |  | 0.97 | | 0.64 | | 0.76 | | 0.59 | | 0.36 | | | | 0.21 | | | | 0.48 | | | | | |
|  |  |  |  |  |  |  |  |  |  |  | |  |  | |  | |  | | | |  | |  | | |  |
| Source: TNS/Kantar |  |  |  |  |  |  |  |  |  |  | |  |  | |  | |  | | | |  | |  | | |  |

Overall, the figures for each brand’s BPMs look much as they should in terms of similarity between brands of similar size. There are however some exceptions—Evans, Mackays and Gap, all in the middle of table. But these deviations can be explained. Evans is a brand catering to large and tall women, or plus sizes. This represents a functional partition in the market based on the physical characteristics of a subset of women shoppers. As a result, the penetration of 100% loyals (37%), purchase rate (4.3) 5 and share of category requirements (49%) are all much higher than for brands of a similar size. In other words, the customers of Evans buy it more heavily than other brands, presumably because it caters to their particular requirements.

Mackays is another exception, in this case it has high purchasing and SCR because it is a big local brand in Scotland, giving it the higher performance measures of a bigger brand, but only in Scotland. It is a regional brand that is big in its region, and absent in the rest of the market. Finally, Gap, while a large international brand, is also a contracting brand, and closed about 25% of its shops between 2011 and 2012. The result for Gap is higher than expected once-only buying, and lower 100% buying loyalty—because closing shops and decreasing distribution make it more difficult to remain loyal. Thus, the exceptions to the general patterns can be explained.

In Table 2, the comparison of competitive brands in the category shows more clearly the underlying structure of the market, where brand performance measures are closely aligned with, indeed predicated upon, the share of the brands. With the non-competitive brands removed, it is easy to observe the high correlations between observed brand performance measures and their theoretical counterparts—listed in the bottom row of figures. Simply casting the eye down the columns however reveals that some slight exceptions to the general run of figures remain; some brands have slightly higher or lower purchases per buyer for example, while others vary in their levels of once only or 5+ buyers. But as with the previous exceptional brands, explanations for the variations in the table could be found. In any case, they are relatively small.

The main conclusion from the analysis of BPMs is that the fashion market has a normal structure, on a par with the structure found in many other consumer goods markets in which the various BPMs for the brands vary together by brand size, and are mainly determined by the market share of the brands. This important step in the analysis allowed us to establish that at least in terms of basic structure, the market does not appear to be exceptional.

Table 2 Competitive Women’s Outerwear Brands

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Observed (O) and Theoretical (T) Brand Performance Measures | | | | | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | Market | Penetration | | Purchase | | % Buying | | | | Category | | 100% Loyal | | | |
| Range | Share | % | | per buyer | | Once | | 5+ | | SCR (%) | | Penetration | | Av Purchase | |
|  | % |  | |  | |  | |  | |  | |  | |  | |
|  |  | O | **T** | O | **T** | O | **T** | O | **T** | O | **T** | O | **T** | O | **T** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Total | 92 | 36 |  | 8.9 |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| New Look | 20 | 15 | **17** | 4.4 | **3.7** | 42 | **43** | 15 | **22** | 33 | **28** | 12 | **13** | 3.4 | **1.5** |
| Other | 19 | 19 | **17** | 3.2 | **3.6** | 50 | **43** | 11 | **22** | 28 | **27** | 21 | **13** | 2.8 | **1.5** |
| Next | 15 | 14 | **14** | 3.5 | **3.4** | 50 | **45** | 11 | **20** | 32 | **24** | 18 | **12** | 3.2 | **1.4** |
| Hennes/H&M | 11 | 9 | **12** | 4.0 | **3.1** | 47 | **48** | 13 | **18** | 26 | **22** | 7 | **11** | 1.8 | **1.4** |
| Dorothy Perkins | 9 | 9 | **9** | 3.0 | **3.0** | 56 | **50** | 7 | **16** | 21 | **20** | 9 | **10** | 2.7 | **1.3** |
| Top Shop | 7 | 5 | **8** | 4.1 | **2.8** | 45 | **51** | 19 | **15** | 22 | **19** | 4 | **9** | 1.8 | **1.3** |
| River Island | 4 | 5 | **5** | 3.1 | **2.7** | 53 | **54** | 9 | **14** | 16 | **17** | 2 | **9** | 1.3 | **1.3** |
| Monsoon | 2 | 3 | **2** | 2.0 | **2.5** | 72 | **56** | 3 | **12** | 18 | **16** | 10 | **8** | 1.9 | **1.2** |
| Miss Selfridge | 2 | 3 | **2** | 2.3 | **2.5** | 58 | **56** | 4 | **12** | 10 | **16** | 4 | **8** | 1.2 | **1.2** |
| Zara | 2 | 3 | **2** | 2.2 | **2.5** | 69 | **56** | 4 | **12** | 12 | **16** | 4 | **8** | 1.2 | **1.2** |
| Wallis | 2 | 3 | **2** | 2.0 | **2.5** | 68 | **56** | 4 | **12** | 20 | **16** | 8 | **8** | 2.0 | **1.2** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Average | 8 | 8 | **8** | 3.1 | **2.9** | 56 | **51** | 9 | **16** | 22 | **20** | 9 | **10** | 2.1 | **1.3** |
| MAD |  | 1 | | 0.5 | | 6 | | 8 | | 4 | | 4 | | 0.8 | |
| Correlation |  | 0.97 | | 0.75 | | 0.78 | | 0.64 | | 0.90 | | 0.74 | | 0.84 | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Source: TNS/Kantar |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

The next step is to perform a duplication of purchase analysis. Again, the process is straightforward and graphically illustrates how brands in the category share their customers. Table 3 is a duplication of purchase table for women’s outerwear. The table can be interpreted by reading across the rows which shows that customers of New Look also bought Other (52%), Next (40%) H&M/Hennes (37%) and so on. Notice that the percentage of New Look buyers who also bought the other brands declines steadily across the table, such that the sharing of customers with other brands is predicated on the size of those other brands. Any brand will share its customers with other brands in line with the size of the other brands. The figures for Zara, for example show that 57% of Zara customers also bought New Look, 71% also bought Other, and 46% also bought Next. The main conclusion from such a table is that women’s wear brands share their customers, and that sharing is in line with the size of the brands.

Table 3, Sharing of women’s outerwear brand customers is in line with market share

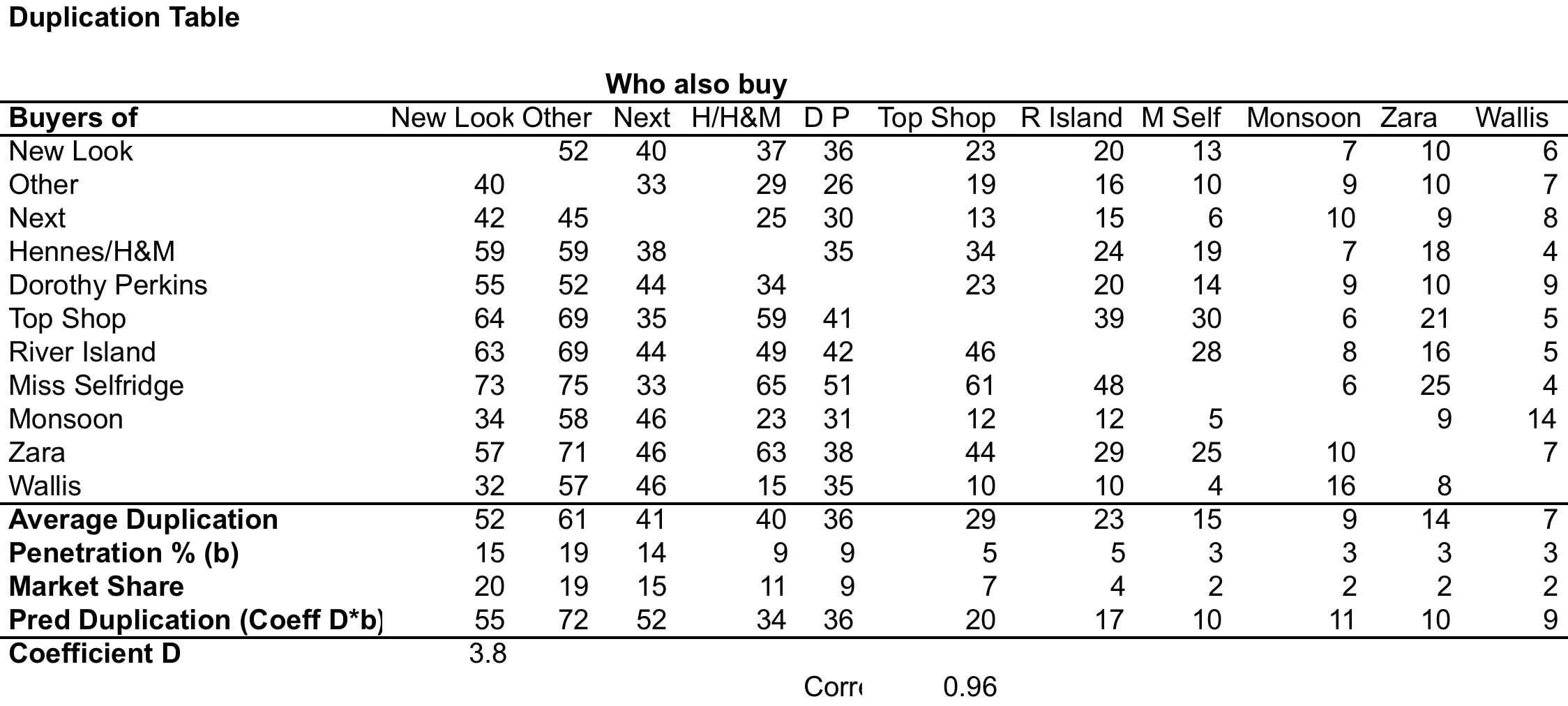


Table 3 can also be read vertically and the figures going down the columns are roughly the same. On average, most brands share about half (52%) of their customers with New Look, 61% with Other and 41% with Next. These average figures decline fairly steadily in step with the size of the brands (Other is a bit out of line because it is a composite of all the small brands in the market). The average duplication for each column in table 3 (the percentage who also bought in the population) shows a very high correlation with brand penetration. Where duplication is high, penetration is also high (for bigger brands on the left) and where it is low, duplication is also low (smaller brands on the right). The correlation coefficient is 0.96. Duplication is about 3.8 times the penetration of the brands. This relationship can be summarized by saying that the portion of brand X buyers who also buy brand Y is approximately equal to a constant (D = 3.8 here) times the proportion of the population who have bought brand Y (brand Y’s penetration). This relationship is an example of the well-known Duplication of Purchase Law (DoP) which has been found consistently in markets round the world. It is represented by the formula:

by/x  = D x by

Where by/x  is the percentage of buyers of X who have also bought Y; D is the constant known as the duplication coefficient; and by is the percent of the population who have also bought brand Y. There are several ways to calculate D. The simplest is to average the duplication percentages (the column averages) and divide that by the average of the penetrations to construct a duplication of purchase table such as Table 4. To interpret the results, recognize that when D = 1, buying one brand makes the purchaser no more or less likely to buy another brand than anyone else in the population—the purchase of one brand has no influence of the purchasing of another brand. However, if the duplication is more than 1, then buying X makes a purchaser more likely to buy Y, and if less than 1, less likely.

Table 4, Duplication coefficients for fashion brands

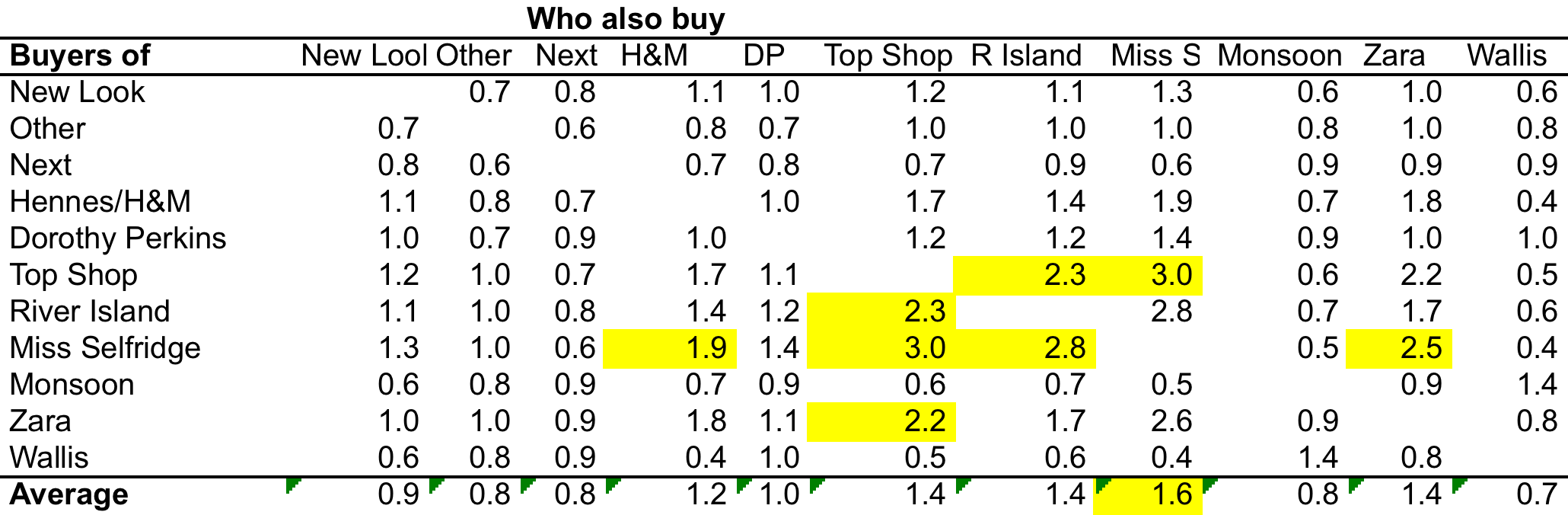


Table 4 shows that for most brands, the duplication coefficients are near to 1. However, there are some exceptions for mostly smaller brands where D is substantially higher. The duplication between Miss Selfridge and Top Shop, for example is 3.0, which can be interpreted as saying that the customers of Miss Selfridge are three times as likely to be customers of Top Shop as the average buyer of women’s outerwear. Moreover, there are some brands that are below 1 and we can see that the customers of Wallis are about half as likely as the population as a whole to also be customers of H&M Hennes or Miss Selfridge. However when interpreting these results it should be remembered that the penetrations of these brands is quite low—less than 10% of all fashion customers buy these brands during the year at all. On the other hand, the larger brands on the left and the top of the table are also the high penetration brands, and their duplications are all much nearer to 1.

The next step is to analyze the buyers of fashion brands.

***Brand User Profiles***

Of primary interest in this study was how the performance of each brand is spread across the various user groups. As mentioned, modern marketing strategies often place heavy emphasis on segmentation and targeting. This as a practical issue, here because women’s outerwear is bought primarily by women. The data were therefore sorted so that the purchase records being examined are those of women who are buying women’s outerwear for themselves. What is of most concern in this analysis however is the comparison between brands. In one respect the variation between brands is simple in that some brands are a great deal larger than others—in other words they appeal to many more buyers. That is the main point of separation between big brands and small brands. Within the customer base of a brand however, it is also possible to calculate what share of particular user groups is captured by particular brands, e.g. do certain brands gain more than the average of younger buyers, or buyers from a particular class. The method for this type of calculation is straightforward. The first step is to calculate the average for all brands in the category for each variable or group under study. Then each brand’s figures can be compared against the average to calculate its difference, or deviation from the average.

This analysis ties together two important marketing concepts, segmentation and brand performance measurement. The link between them is straightforward conceptually. Consider a brand that targets a particular user group—younger women for example. If the strategy is successful, then a higher proportion of its user base will be younger women, compared to its competitors. This would be confirmation of brand-level segmentation. In the same manner, if a brand is successful in its appeal to that particular user group, then this should be reflected in a higher market share among that group than in the rest of the market. Examination of a brand’s market share along these dimensions in the market generally, and amongst buyer subgroups (e.g. specific demographic groupings) simultaneously indicates any brand-level segmentation as well as broader measures of overall brand performance.

In this case the main point of interest is the market composition of category buyers. The analysis is straightforward: each brand’s market share is compared within each demographic group. Table 5 illustrates the process of data analysis used for age groups. The Total row is the sum of all users across all eleven brands. Percentages are calculated from the raw data to standardise for different numbers of users. The average of each variable is calculated for each product category, as shown in the bottom row, labeled ‘average.’

Table 5. Market share of age groups for competitive brands

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | up to 24 | 25-34 | 35-44 | 45-54 | 55 plus |
|  |  |  |  |  |  |  |
| New Look |  | .53 | .19 | .12 | .10 | .07 |
| Other |  | .37 | .21 | .15 | .18 | .11 |
| Next |  | .13 | .21 | .25 | .24 | .18 |
| Hennes/H&M |  | .50 | .24 | .10 | .08 | .08 |
| Dorothy Perkins |  | .34 | .33 | .18 | .11 | .05 |
| Top Shop |  | .64 | .16 | .06 | .03 | .01 |
| River Island |  | .53 | .19 | .14 | .12 | .02 |
| Monsoon |  | .11 | .17 | .22 | .22 | .28 |
| Miss Selfridge |  | .70 | .17 | .06 | .06 | .02 |
| Zara |  | .39 | .22 | .17 | .17 | .06 |
| Wallis |  | .13 | .10 | .19 | .48 | .10 |
|  |  |  |  |  |  |  |
| average |  | .40 | .20 | .15 | .16 | .09 |
|  |  |  |  |  |  |  |

Table 5 shows how the attractiveness of each brand is spread across user groups defined by age. The ordinary practice in marketing is to develop a target audience (or targets) for marketing communication. And while there is much evidence that this is the norm, the data presented here do not capture information about the groups targeted by these individual brands (though it could conceivably be added extraneously). Rather, the data show the spread of each brand’s market share amongst the age groups (or other classifications). From this it is possible to make some inferences about marketing or targeting strategies. In the table, the brands are organized as before by size from largest to smallest, and across the table the age breakdowns available in the data. The average figures at the bottom show that for women’s outerwear, about 41% of the customers are up to 24 years old, 20% are between 25 and 34, 15% are between 35 and 44 and so on. By comparing each brand against the average, it is immediately clear that all brands have customers from every age group, but some brands (New Look, Miss Selfridge) have higher than average shares of younger customers, and others (Next, Monsoon, Wallis) have below average shares. Looking at the other age groups shows that these same brands capture a higher than average share of older age groups.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |

Table 6. Mean Absolute deviations for age groups

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | up to 24 | 25-34 | 35-44 | 45-54 | 55 plus |
|  |  |  |  |  |  |  |
| New Look |  | .12 | .01 | .03 | .07 | .02 |
| Other |  | .04 | .01 | .00 | .01 | .02 |
| Next |  | .24 | .01 | .10 | .07 | .09 |
| Hennes/H&M |  | .10 | .04 | .05 | .09 | .01 |
| Dorothy Perkins |  | .06 | .13 | .03 | .06 | .04 |
| Top Shop |  | .23 | .04 | .09 | .13 | .07 |
| River Island |  | .13 | .01 | .01 | .05 | .07 |
| Monsoon |  | .28 | .03 | .07 | .05 | .19 |
| Miss Selfridge |  | .30 | .03 | .09 | .11 | .07 |
| Zara |  | .01 | .02 | .02 | .00 | .03 |
| Wallis |  | .27 | .09 | .07 | .32 | .02 |
|  |  |  |  |  |  |  |
| MAD (overall average = .08) |  | .14 | .04 | .05 | .09 | .06 |

The Average is used to calculate deviations for each brand. Deviations can be positive when the brand has more users than the average for the product category, or negative when they have fewer users in that category. To enable a comparison on the magnitude of deviations across the category the Mean Absolute Deviations (MADs) are calculated. This averages the absolute variation (whether negative or positive). To calculate the MAD, absolute values for each brand are used so that negative and positive deviations do not cancel each other out. Then the absolute deviations are averaged across all brands reflected in the MAD in the last row.

The MADs for shares of different social classes of buyers and for self-described fashion-orientation are shown in Table 7. Compared to age groups, brands deviate from the category average much less on social class and fashion orientation. In other words, most brands attract close to the average share of their customers from the various social classes and fashion orientations, deviating on average only 6 points. As with age groups, all brands draw their customers from all social classes and fashion orientations.

Table 7. Mean absolute deviations for Social class, and fashion lifestyle

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |
|  | **Social class** |  |  | AB | C1 | C2 | DE |  | MAD |
|  | Share% |  |  | 22 | 35 | 27 | 17 |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  | Average deviation |  |  | 0.02 | 0.05 | 0.05 | 0.06 |  | .05 |
|  |  |  |  |  |  |  |  |  |  |
|  | **Fashion Orientation** |  |  |  |  |  |  |  |  |
|  |  |  |  | Stylish | Budget | Upmarket | Other |  |  |
|  | Share % |  |  | 56 | 17 | 15 | 13 |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  | Average deviation |  |  | 0.09 | 0.03 | 0.04 | 0.04 |  | .05 |
|  |  |  |  |  |  |  |  |  |  |

To address the research question of whether there are differences in consumer profiles between brands in the same product category, the distribution of absolute deviations across all socio-demographic characteristics and all brands was analyzed. Results in Table 8 suggest an L-shaped distribution with a large number of small deviations (42% below 2pp) and a long tail of few large deviations. Only 11% of the brand deviations were larger than 10pp.

Table 8. Summary Mean Absolute Deviations

In summary, the analysis demonstrated that the brands in the womens outerwear market are very similar to brands in other categories in terms of their brand performance metrics. More detailed analysis of demographic variables to explore whether the brands attract different types of customers revealed mostly very small variations between brands in their customer bases. The only exception to this was that some brands were able to attract a higher portion of the very youngest age group (up to 24 years old). Most other age groups did not have high deviations.

**5. Discussion and Implications**

This study examined key brand performance metrics in a product category that gets much attention in the press, but less research. Based on the positioning of the brands, and commentary from other authors it might have been expected to see that some brands in this category would exhibit exceptional patterns in their performance metrics than has been published in previous research. However, this research showed the opposite. Brands in the ladies outerwear category, including some of the most famous and successful brands, exhibit; a) polygamous loyalty with buyers allocating a share of their purchase requirements across brands over time, including the double jeopardy effect; b) spread their purchases across a number of shops approximately in line with the market share of the other shops, as per the duplication of purchase law and c) approximately equal performance amongst the demographic subgroups, in other words the appeal of all brands was approximately equal across demographic subgroups, with a small exception that some brands were more or less appealing to younger buyers. Overall, an average deviation of 5 percentage points in the sociodemographic profiles between brand buyers of women’s outerwear. This average deviation is in line with similar findings for other markets (Kennedy & Ehrenberg, 2001b; M. Uncles, et al., 2012).

***The implications of this research.***

The findings suggest that, as in other categories and markets, fashion brands user profiles rarely differ. This suggests that competition to retain users and the potential for new users is not restricted to sociodemographic segments. Marketers should aim to capture the entire market. This does not mean that positioning or product variation are not important to appeal to different needs or tastes. Specific requirements can be provided within a brand. It should also be mentioned that while some brands did manage to appeal more to the youngest age group—in other words, they focused on teenagers—yet even these brands also attracted customers from all other age groups.

For researchers, this study highlights that brand performance needs to be analysed in context. One cannot interpret brand performance metrics such as loyalty or switching without recourse to the established patterns found over decades of academic research on the topic (listed in the introduction). The discussion of results also highlights a potential danger in focusing too much on differences in brand performance among buyer groups. A brand might well show higher or lower performance in a particular buyer group, but if that buyer group accounts for only a small proportion of total sales, it presents limited scope for action.

There are also important implications for brand managers. First, in order for a brand to grow, it will probably need to grow its market share ‘across the board’ – that is, increase its sales to a broad range of demographic groups. Focusing on one narrow target group may be counterproductive, because it will limit the ability of the brand to grow. Managers should appreciate the brands in their category will probably exhibit some differential appeal across various buyer groups, but such differentials are likely to be small, and even if a brand is more popular with one subgroup, that does not mean it is unpopular with others. Managers also need to appreciate that their brand competes against all others in their category, and it is the other largest brands that they share their customers with the most. Nor should managers be perturbed that their customers only allocate a small share of their category requirements to their brand. Even the buyers of the biggest, most dominant brands give them (only) a *share* of their purchases over time. Finally, the ‘double jeopardy’ effect gives some context to the loyalty exhibited towards a brand. A manager of a small brand should not be perturbed that loyalty to their brand is a bit lower than for larger brands in the category. In the same vein, a manager of a big brand should not be complacent that their brand gets somewhat greater loyalty compared to its smaller competitors – this is to be expected and appears to be a natural outcome of having high market share.

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