MODELLING THE IMPACT OF SOCIO-DEMOGRAPHIC SEGMENTATION ON GROCERY STORE PATRONAGE

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Abstract

Previous research has shown that for competing stores both store patronage and store loyalty are well predicted by the very general NBD-Dirichlet model. This finding not only highlights the regularity and predictability of many aspects of store patronage, but also provides a benchmark for further analyses. In this paper we use the NBD-Dirichlet model as a benchmark to assess the impact of socio-demographic segmentation on grocery store patronage and loyalty. We focus on primary grocery shopping visits in one US city. The data are from IRI scanner-panel household shopping records for a two year period.

For each segment within four socio-demographic categories, we compare the observed patterns of patronage and loyalty with the model fitted to each segment. We use relative mean absolute deviations (RMADs) to assess the degree of observed segmentation between competing stores. We find that market share is the dominant factor in the explanation of differences in patronage and loyalty between stores, and that while socio-demographic factors are often important their impact is secondary.
1. Renewed Interest in Loyalty-Based Customer Segmentation

The measurement of customer loyalty to brands is one of the most common themes in the marketing press, with both manufacturers and retailers striving to sustain the loyalty of their customers in the face of competitive market pressures. Indeed, long-term loyalty has now become the focus of a management philosophy (Reichheld 1993, 1996) embracing not only consumers but also staff and investors. Reichheld claims that the most successful companies show a high(er) level of customer and staff retention, which then feeds through into high(er) profitability. This type of managerial thinking is implicit in the increasing use of “customer continuity programmes” - reward schemes, loyalty programmes, affinity cards, and frequent-buyer programmes.

To a significant extent, this interest in loyalty is not new. “Frequent-flyer” airline programmes have been well-established since the 1980s. Grocery chains have issued stamps (such as S & H Green Stamps) for decades. But what we now see is packaged goods companies and retailers showing renewed interest in establishing “relationships” with their customers, as noted by Uncles (1994); “Major schemes are being launched constantly, often with the same sort of “fanfare” that was once reserved for new product launches, store openings, new advertising campaigns and high profile promotional offers”.

What we also see is the pervasiveness of these schemes. For example, grocery chains from such diverse markets as the UK (Mintel 1995), Italy (Castaldo and Mauri 1993), Australia (Dowling and Uncles 1997, Sharp and Sharp 1997) and Japan (Worthington 1994) have launched high-profile schemes in recent years. Underlying these developments are three widely-held beliefs about the behaviour of customers:

1. In most markets there is a discrete segment of buyers who are loyal. That is, some customers consciously and deliberately choose one brand or store rather than another, and they continue to choose in this way time and again. Furthermore, it should be possible to make these loyal buyers even more loyal by ratcheting them up a “loyalty ladder”.

1
2. This segment of loyal buyers can be targeted, i.e. it is possible to identify them, not just in terms of their values or lifestyles but by broad demographic criteria (age, sex, etc.) or even as individual households (household level data can be collected through a customer loyalty card scheme).

3. This segment of loyal buyers is a profitable target group. That is, these customers are both numerically large, and are heavy or frequent buyers with significant purchasing power (in stating this belief most marketers would have the 80:20 rule in mind, i.e. that 80% of sales are generated from 20% of buyers).

These assumptions form the basis of loyalty-based consumer segmentation schema (e.g. Knox 1996, Walker and Knox 1995). Despite the intuitive appeal of these schema, and their popularity in management, evidence to support the three key assumptions is equivocal. We contribute to this debate by studying how these assumptions relate to our existing knowledge of loyalty in general, and loyalty-based consumer segmentation in particular. The purpose of this paper, then, is to explore the underlying behavioural basis for loyalty schemes in grocery retailing, not to comment on the schemes themselves.

1.1 Customer Loyalty to Grocery Stores

There is extensive empirical evidence that, for frequently-purchased products, buyers tend to have a portfolio of brands from which a particular purchase is made (Cunningham 1956; Ehrenberg 1988; Uncles et al. 1994). However, customers do not spread their purchases evenly across the brands they buy, in the long run, one brand may be preferred and will be bought more than others. This pattern of brand purchase also extends to grocery store choice - customers have a portfolio of stores they patronise, some more often than others, making, on average, between one and two visits a week (Cunningham 1961; Frisbie 1980; Kahn and Schmittlein 1989; Kau and Ehrenberg 1984; Uncles and Hammond 1995; Wrigley and Dunn 1985).
Research into store choice has mostly concentrated on the behavioural aspects of store loyalty, e.g. the average interval between store visits, the average spend, the average number of stores visited over a year, and how many customers shop at one store only over a year (Cunningham 1961; Burford, Enis and Paul 1971; Frank 1967; Uncles et al. 1994). Previous research has also searched for customer characteristics that discriminate store-loyal households from others. However, findings have been weak and conflicting. High store loyalty has been associated with low income (Carman 1970; Dunn and Wrigley 1984; Enis and Paul 1970) and fewer years of education for the shopper (Carman 1970; Enis and Paul 1970), but these findings were not replicated in two recent UK studies (East et al. 1995; Mason 1991). If the female head of household is in employment this has been found to predict higher store loyalty in two studies, (Carman 1970; Mason 1991), but not in a third study (Dunn and Wrigley 1984). The age of the principal (female) shopper was a predictor of loyalty in one study (East et al. 1995) - but again it is unclear whether this is a general finding.

**1.2 Customer Segmentation and Loyalty to Grocery Stores**

We know that customers differ widely in their individual store choices, their frequency of store visits, amount spent and levels of store loyalty. The levels of patronage and loyalty to individual stores have been shown to vary in line with the store’s market share (Uncles and Hammond 1995). But do competing stores have different levels of patronage or loyalty, *independent of their size*? If yes, *are these differences related to socio-economic factors*?

Our focus in this paper is whether such heterogeneous customers can be classified into relatively homogeneous segments in terms of their store choice. There has been very little research which has looked specifically at this issue of the consumer profiles of shoppers who patronise different stores, i.e. store segmentation. In the area of *brand segmentation*, it has been shown that brands which are broadly similar are generally not bought by
different segments of the population (Hammond et al. 1996). In this paper we report on an analysis of household panel data aimed at establishing the extent of *store segmentation*. 
2. The Empirical Study

2.1 Data

The data come from nine competing grocery stores in one market. The stores include branches of national grocery chains, a regional chain, co-op stores and independent grocery outlets. The market was Rome, Georgia, USA and the data were supplied by Information Resources Inc. (IRI). Each store visit for 466 households on a panel was recorded over a period of two years. The average household made two store visits a week, giving around 97,000 household shopping records. Households’ store visits were divided into primary and secondary visits. The average (median) spend per visit across all stores in this market was $11. A primary visit was defined as one where the spend was $13.75 or more, and a secondary visit where the spend was $8.25 or less. In this paper we report results for primary shopping visits only. From the data we were able to calculate a range of behavioural measures relating to store visits:

(a) store patronage (the percentage of households making at least one visit to the store during a specific period),

(b) frequency of store visits (within a specific period),

(c) repeat-visits (percentage of store shoppers who return to that store in the following period),

(d) share of category requirements (for customers of a store, the percentage of total grocery shopping visits accounted for by that store).

We calculate each of these measures for a number of shopper segments, using available (and typical) demographic criteria (e.g. size of household, household income, age of female head of household, and work status of female head of household). The demographic segments were:

(a) household size (4 segments: one-person household, 2-person, 3-person, 4+ person household),
(b) household income (4 segments: lowest third of households, low-medium average income, medium-high average income, highest 15%),

(c) age of female head of household (3 segments: 18-44 years, 45-64 years, 65+),

(d) work status of female head of household (3 segments: no work outside the home, part-time employment, full-time employment).

2.2 Research Strategy

1. Descriptive analysis of the extent and nature of store segmentation, across a number of different store types, using a range of behavioural measures. The degree of segmentation between competing stores is summarised using relative mean absolute deviations (RMADs). RMADs show the relative absolute deviation between the results for an individual store measure compared with the results for the average store measure.

2. Comparison of empirical data with model predictions. We use the NBD-Dirichlet model to provide benchmark figures or “norms” for the behavioural measures for each segment. These Dirichlet norms are based on the market share for that segment.

2.3 The NBD-Dirichlet Model

The NBD-Dirichlet is a stochastic model of buyer behaviour which was originally developed for the study of branded packaged goods in established competitive markets (Chatfield and Goodhardt 1975; Bass et al. 1976; Goodhardt et al. 1984; Ehrenberg 1988). The theory underlying the Dirichlet is that there is a small set of interrelated assumptions which describe and predict the patterns of purchase incidence and brand choice for any market which is approximately stationary, unsegmented and non-partitioned (Ehrenberg and Uncles 1997).
The usefulness of this model as a benchmark lies in the fact that it has successfully characterised the detailed structure of consumer markets *in general* across a wide range of conditions. For example, Dirichlet-type patterns have been found to occur for: approximately 50 different food, drink and other grocery products, including private labels; OTC medicines; gasoline; motor cars; TV programs and channels; store chains and shopping visits; in the UK, US, Japan and Germany; for different time periods (from one week to two years, for data from 1950-1996), and different data collection methods (Ehrenberg and Uncles 1997). In this paper we build on earlier work which uses the NBD-Dirichlet to model the incidence of store visits and store choice (Uncles and Hammond 1995), combined with research which has used MADs to summarise consumer segmentation profiles (Hammond *et al.* 1996).

2.4 Model Specification

The incidence of store visits is specified as a mixture of:

(i) Poisson distributions (for each shopper), and a

(ii) Gamma distribution (for the means of the Poissons across shoppers).

This gives rise to a Negative-Binomial Distribution (NBD) for the number of store visits made in a time-period of length $T$, with mean $MT$ and exponent $K$. The indexing by time $T$ enables predictions to be made for different length time periods, although in this paper, as a simplification, we will report theoretical results for 1 year only (with empirical results calculated as the average of two 1-year periods).

In terms of store choice each shopper is assumed to have a set of “propensities” for visiting given stores which are expressed as a set of probabilities. We assume a mixture of two probability distributions, to give the number of visits, $r$, which a shopper makes to a particular store, given that s/he makes $n$ store visits in all. The distributions are that:
(iii) each shopper’s probability, p, of visiting a given store is constant over time and follows a multinomial distribution $M(r | p, n)$, and

(iv) the distribution of such probabilities, p, among shoppers follows a “Dirichlet” type of multivariate Beta Binomial distribution $D(p | \alpha)$. Here $D(p | \alpha) = C p_1^{\alpha_1-1} \cdots p_g^{\alpha_g-1}$ for g stores, where the $\alpha$ are proportional to the stores’ market shares and where they add to the parameter, $S$ (as noted below), and C is a scaling coefficient which is a function of the $\alpha$. By grouping terms we obtain the compound distribution:

$$[M(r | p, n) \hat{p} D(p | \alpha)] \hat{n} [P(n | \mu) \hat{\mu} G(\mu | MT, K)]$$

Where $M$, $D$, $P$ and $G$ denote the Multinomial, Dirichlet, Poisson and Gamma distributions. Since the model is for unsegmented markets, it is assumed that the above statistical distributions are independent of each other. A further assumption is that all stores are able to compete with each other. In this study all the stores operate within one very discrete geographical market, and the assumption that all stores compete directly is justified.

2.5 Model Estimation

The model is parsimonious in its input requirements. It is necessary to estimate the mean rate of purchasing, $M$, and the exponent, $K$, of the NBD. The Dirichlet component has one parameter, $S$, (sometimes called the “switching” parameter). $S$ is the sum of the values of $\alpha$s in the model, and reflects how diverse shoppers are in their store choices. This parameter can be estimated simply from: (a) two measures relating to the whole grocery market in the city: overall patronage (which will be 100% in the case of retail patronage, except in short time periods) and the average shopping frequency of shoppers, and (b) these same two measures for each, or any, of the itemised stores. There are no closed algebraic formulae, so the estimation of the model’s parameters is essentially arithmetic.
The parameter K is calculated by fitting an NBD to the distribution of purchases for the total product class. We use the mean and zero method of estimation by solving \(1-B = (1+M/K)^k\) for K, where B is the proportion of the population making any store visit in a given time period. In a study of shopping visits there are very few non-shoppers, an alternative here would be to calculate K using the mean and moments method.\(^1\)

2.6 Validation

1. There is strong support for the use of this model. Routine tests can be performed to check the assumptions. Here we are not dealing with abstract or normative assumptions. Any violations of the assumptions will appear as deviations (for example, if there is store segmentation based on the demographic profile of the shoppers, the values for store patronage and loyalty variables for different stores will show systematic deviations from the model predictions which are based solely on the store’s market share).

2. The order of the model (zero-order) and distributional properties are well-known and accepted (Bass et al. 1984; Dunn et al. 1983; Morrison and Schmittlein 1988). In principle, alternative models might be applicable (e.g. several papers from Morrison 1969 onwards have proposed various conditional NBDs) or we might consider non-parametric specifications of heterogeneity (e.g. Reader and Uncles 1988; Reader 1993), but these alternatives do not have either the general or the parsimonious appeal of the NBD-Dirichlet. A direct comparison of parametric and non-parametric methods in a previous store choice study showed a negligible improvement in fit from using the mass point estimation method (Reader and Uncles 1988). From a practical point of view it is not felt that the additional computation and loss of generality of the findings justifies the use of non-parametric alternatives in studies such as this.

\(^1\) This alternative method was not used in this study; it is computationally more complex, and previous experience suggests that although different methods slightly alter the precise value of the predictions, the differences are minor and the substantive conclusions do not alter.
3. We make an assumption that the market is stationary over the analysis period, i.e. we assume that aggregate market shares remain broadly constant. In the case of the data analysed here we empirically checked that this assumption was valid - market shares for the different stores fluctuated considerably week by week, but in the medium term (e.g. on a quarterly or annual basis) were extremely stable. This does not mean that there is not variability in the data. Underlying these stationary market shares there is advertising activity, price promotions, etc., but on average, and in aggregate, such marketing activity serves to stabilise market shares, and so a stationary model is well-suited to explaining brand behaviour over the medium term.

4. With regard to the goodness-of-fit, studies of packaged goods markets have shown consistently that the NBD-Dirichlet is a good predictor (e.g. results for thirty-four product fields are reported in Uncles et al. 1994). However, in this paper we focus on using the NBD-Dirichlet model as a benchmark, rather than testing the fit of the model, we therefore do not report model fit measures. Bearing in mind the advantages of parsimony that the Dirichlet brings, we are seeking a “generally good fit” across many sets of data (different stores and store chains) rather than the “best fit” which might be achieved in OLS regression using only one set of data.

3. Results

To illustrate our approach we concentrate first on patronage and loyalty measures for three of the nine stores, each typical of a different type of retail environment, plus results for the average store. Store A belongs to a national chain, Store C is a Co-op store, and Store I is an independent store. Table 1 shows the average yearly results (average of two years) for primary shopping visits made by all households in the dataset. From the top line in the Table, we see that, for the average store, 40% of households visited it at least once during the year. If they patronised a store, then on average, they made 13 visits to that store. 78% of shoppers visited the same store again the following year, and on average, that store satisfied 26% of their shopping requirements.
If we look down the columns in Table 1, we see how individual stores vary by patronage and loyalty. Store A has more shoppers than Store C or Store I (53% visiting at least once versus 38% and 34% respectively). Shoppers at Store A also shop there more often (19 times a year compared to 16 times for Store C and 7 times for Store I), and for these shoppers, Store A accounts for a larger percentage of their shopping requirements (39% compared with 31% at Store C and 15% at Store I). These findings can be linked to market share differences between the three stores. The Co-op store in our example (Store C) is smaller than the national chain store (Store A) and therefore has fewer people visiting it in a year. Those who do visit shop there less often and that store satisfies slightly less of their shopping requirements. This exemplifies the well-established Double Jeopardy phenomenon which has been shown to exist across a wide range of choice behaviours (Ehrenberg et al. 1990; Uncles et al. 1995).

If we turn to repeat patronage, this trend with market share is not so obvious; Store I has a repeat-patronage rate of 70%, this seems fairly high, but it is lower than for stores A and C. However, Store C has a higher rate of repeat patronage than Store A, 82% versus 79%. It is very difficult to gauge just from the empirical data whether these findings are in line with the law of Double Jeopardy, or whether some stores have excess or lower loyalty than expected.

3.1 Model Fit

<table>
<thead>
<tr>
<th>Market Share %</th>
<th>% Visiting at least once (patronage)</th>
<th>Average number of visits</th>
<th>% Repeat patronage</th>
<th>% Share of category requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Store</td>
<td>40</td>
<td>13</td>
<td>78</td>
<td>26</td>
</tr>
<tr>
<td>Store A</td>
<td>19</td>
<td>53</td>
<td>19</td>
<td>79</td>
</tr>
<tr>
<td>Store C</td>
<td>13</td>
<td>38</td>
<td>16</td>
<td>82</td>
</tr>
<tr>
<td>Store I</td>
<td>4</td>
<td>34</td>
<td>7</td>
<td>70</td>
</tr>
</tbody>
</table>

Source: IRI, 406 households, yearly data, average of 1984/85
In Table 2, we present results for all nine stores, plus Dirichlet predictions and RMADs. The Dirichlet model is fitted to the overall market (rather than to any specific store or stores). The only store specific input is the market share of each store. The other general input needed is the overall store-visit frequency in this market. From these inputs the model gives predictions for a range of patronage and loyalty measures for each store based only on that store’s market share. Therefore any systematic deviations from the model predictions will suggest that market share is not the most important factor in determining store loyalty, i.e. there is segmentation (or some other cause).

From Table 2 we can see that the model generally performs well in picking up the trends for each measure, but there are some discrepancies. On average the model predicts the overall store patronage very well (40% predicted versus 40% actual), however we can see that for the larger stores the model tends to over-predict patronage (e.g. 66% predicted versus 53% observed for Store A; 47% predicted versus 34% observed for Store D), while for smaller stores the model under-predicts patronage (e.g. 23% predicted versus 34% observed for Store I). There are corresponding discrepancies (in the opposite direction) for the average number of visits and for the percentage of category requirements satisfied by each store. The model also appears to over-predict (almost systematically) the percentage of repeat shoppers from one year to the next. The correlation between predicted and observed values for the patronage measure is (r=0.75), for average number of visits (r=0.85), for repeat patronage (r=0.72), and for share of category requirements (r=0.86).
The final row in Table 2 reports the relative Mean Absolute Deviation (RMAD) for each measure. The RMAD scores reflect how different, on average, the results for each measure for the individual stores are from the results for the average store. The smaller the RMAD the less the difference in the measure across stores. However, we know that, according to the law of Double-Jeopardy, a store’s loyalty and patronage depend on its market share. We therefore expect to see differences across stores in both the observed and predicted values for all four measures. These market share trends are predicted by the Dirichlet, so it is most meaningful to compare the RMADs for the observed results with the RMADs for the Dirichlet predictions.

For the patronage measure, the RMAD for the Dirichlet predictions is greater than that for the observed values (18% observed, 30% predicted), which certainly suggests no store segmentation (if store segmentation existed we would expect the RMAD for the observed values to be greater than that for the predicted). For the other three measures the RMADs

Table 2: Measures of Patronage and Loyalty at Different Competing Stores
Rome, Georgia, US primary shopping visits over 52 weeks

<table>
<thead>
<tr>
<th>Market share</th>
<th>% Visiting at least once (patronage)</th>
<th>Average number of visits</th>
<th>% Repeat patronage</th>
<th>% Share of category requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>O D</td>
<td>O D</td>
<td>O D</td>
<td>O D</td>
</tr>
<tr>
<td>Av. Store</td>
<td>40 40</td>
<td>13 10</td>
<td>78 87</td>
<td>26 24</td>
</tr>
<tr>
<td>Store A</td>
<td>19 53 66</td>
<td>19 13 13</td>
<td>79 90</td>
<td>39 31</td>
</tr>
<tr>
<td>Store B</td>
<td>16 59 55</td>
<td>13 11 11</td>
<td>93 90</td>
<td>27 27</td>
</tr>
<tr>
<td>Store C</td>
<td>13 38 46</td>
<td>16 10 10</td>
<td>82 88</td>
<td>31 25</td>
</tr>
<tr>
<td>Store D</td>
<td>12 34 47</td>
<td>18 11 11</td>
<td>83 87</td>
<td>37 25</td>
</tr>
<tr>
<td>Store E</td>
<td>11 36 31</td>
<td>10 9 9</td>
<td>80 86</td>
<td>20 22</td>
</tr>
<tr>
<td>Store F</td>
<td>10 34 41</td>
<td>15 10 10</td>
<td>72 87</td>
<td>30 24</td>
</tr>
<tr>
<td>Store G</td>
<td>8 34 25</td>
<td>8 9 9</td>
<td>75 84</td>
<td>17 21</td>
</tr>
<tr>
<td>Store H</td>
<td>7 37 27</td>
<td>8 9 9</td>
<td>66 85</td>
<td>17 21</td>
</tr>
<tr>
<td>Store I</td>
<td>4 34 23</td>
<td>7 9 9</td>
<td>70 84</td>
<td>15 21</td>
</tr>
</tbody>
</table>

RMAD % 18 30 9 2 30 10

Source: IRI, 406 households, O=Observed data, D=Dirichlet predictions
RMAD: Relative Mean Absolute Deviation. MAD= (sum (average store - individual store))
for the observed values are higher than for the predicted ones, which suggests that there is greater segmentation across stores than the model predicts.

Although the model performs well at the aggregate level, we have shown that there are differences by store, beyond those we would expect due to market share variation. The next question is whether these differences reflect targetable differences in the clientele of the stores, e.g. are there systematic differences by household income, age of shopper, household size or work status of the main shopper?

3.2 Segmentation Example (by Age of Shopper)

We illustrate the degree of segmentation found by showing first the results for just one of our segmentation criteria. We have chosen the age variable since the results for age show the most extreme segmentation. Shoppers were divided into three segments according to the age of the main female shopper in the household. Segment 1 included shoppers aged 18-44 years, segment 2 shoppers 45-64 years and segment 3 those 65 years or over. For the average store, 30% of shoppers were in the first age group (under 45), 45% were 45-64 and 25% were 65+.

Obviously there is a degree of subjectivity about where we have chosen to divide our sample, but we have followed previous research and what seemed intuitively sensible to us.

In Table 3, the empirical figures for each measure, together with Dirichlet predictions and RMADs are given for the average store and for the leading store, Store A. The Dirichlet predictions reported here were as follows: (a) one model was specified for all stores (and the results for this model can be seen in the rows labelled Av. Store and Store A), (b) additionally we have three separate models for each age segment (Age 1, Age 2, Age 3).
We see that the models fit the data fairly well. If we look at the individual segments for Store A, the model generally picks up trends - the exception being for the repeat patronage measure for the Age 3 segment where the low repeat rate of 64% is not well captured by the model.

We can see how different each segment is from the average household by looking at the RMADs. If we look at Store A, there is more variability between the segments than for the average store and this is reflected in larger RMADs. For Store A, the RMADs for the observed data are higher than for the Dirichlet predictions for the repeat patronage measure, but there are not significant differences in the RMADs for the other measures. Does this pattern generalise across all stores and for other segmentation criteria?

Table 3: Measures of Patronage and Loyalty by Age
Rome, Georgia, US, primary shopping visits over 52 weeks

<table>
<thead>
<tr>
<th>Age</th>
<th>Market share</th>
<th>% Visiting at least once</th>
<th>Average number of visits</th>
<th>% Repeat patronage</th>
<th>% Share of category requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>O</td>
<td>D</td>
<td>O</td>
<td>D</td>
<td>O</td>
</tr>
<tr>
<td>Av. Store</td>
<td>40</td>
<td>40</td>
<td>13</td>
<td>10</td>
<td>78</td>
</tr>
<tr>
<td>Age 1</td>
<td>30</td>
<td>40</td>
<td>39</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>Age 2</td>
<td>45</td>
<td>42</td>
<td>42</td>
<td>14</td>
<td>13</td>
</tr>
<tr>
<td>Age 3</td>
<td>25</td>
<td>38</td>
<td>38</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>RMAD</td>
<td>3</td>
<td>4</td>
<td>12</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>Store A</td>
<td>19</td>
<td>53</td>
<td>66</td>
<td>20</td>
<td>13</td>
</tr>
<tr>
<td>Age 1</td>
<td>30</td>
<td>63</td>
<td>79</td>
<td>24</td>
<td>16</td>
</tr>
<tr>
<td>Age 2</td>
<td>20</td>
<td>56</td>
<td>65</td>
<td>20</td>
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<tr>
<td>Age 3</td>
<td>14</td>
<td>41</td>
<td>47</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>RMAD</td>
<td>15</td>
<td>17</td>
<td>21</td>
<td>23</td>
<td>10</td>
</tr>
</tbody>
</table>
3.3 Summary Results Across All Segmentation Criteria

Table 4 summarises the results across all three store types - national chains, co-op stores and independents - and all segmentation criteria. Store types are used rather than all nine stores purely for ease of presentation, the results are very similar if individual stores are studied. The results are presented as RMADs across store types and across segments. We can see that the RMADs differ little across the different socio-demographic factors. The RMADs for the observed values are in the range 5% to 22%.

In order to gauge the extent of segmentation captured by the RMADs we ran a Chi-square test on a number of the segmentation variables. Using Chi-square we tested how different the expected segmentation was from the actual segmentation for both the observed data and the Dirichlet predictions. For the Age variable, for the patronage measure, the observed RMAD is 8; there is no significant difference in the patronage values between the age segments for this variable. The Dirichlet RMAD is 14; here there is a significant difference in patronage values between age segments at the p>.01 level. If we turn to the work status measure, the patronage RMADs are 8 (observed) and 13 (predicted). There are no significant differences in the patronage values between work status segments for either the observed or predicted values. Obviously significant differences depend on the size of the sample population, but we now have some feel for how to evaluate differences in RMADs.

### Table 4: Store Segmentation: Relative Mean Absolute Deviations (RMADs)

Rome, Georgia, US, primary shopping visits over 52 weeks

<table>
<thead>
<tr>
<th>% Visiting at least once (patronage)</th>
<th>Average number of visits</th>
<th>% Repeat patronage</th>
<th>% Share of category requirements</th>
</tr>
</thead>
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<table>
<thead>
<tr>
<th>Segmentation by store type compared with average store</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 Types*</td>
</tr>
<tr>
<td>16 23 21 7 6 21 8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segmentation within each store by socio-demographic factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household size</td>
</tr>
<tr>
<td>11 19 18 16 5 2 17 7</td>
</tr>
<tr>
<td>Age of shopper</td>
</tr>
<tr>
<td>8 14 15 13 5 1 13 6</td>
</tr>
<tr>
<td>Work status</td>
</tr>
<tr>
<td>8 13 11 12 5 1 10 4</td>
</tr>
<tr>
<td>Income</td>
</tr>
<tr>
<td>11 17 22 20 6 2 17 6</td>
</tr>
</tbody>
</table>

*Three store types - National chain, Co-op and Independent
Store type appears to be more of a differentiator than demographic characteristics; the RMADs for the observed values by store type are all higher than the average socio-demographic RMADs.

4. Discussion

In this paper we have reported results for primary shopping visits; however, additional analyses show that these results hold for secondary (low spend) grocery shopping visits, and for “average” (medium spend) visits. It is a more open question whether the results apply to other segmentation criteria - we have deliberately concentrated on the type of socio-demographic criteria typically used in market research practice.

Market share still appears to be the dominant factor in explaining differences in patronage and loyalty between stores. In this paper we have used the Dirichlet model (a model of a stationary market) as a tool to help us understand and interpret differences within a potentially segmented market. Without allowing for market share, we would not be able to interpret our segmentation results, but the model shows, for each measure, which results are in line with what we would expect, and which show up true segmentation. We did find differences between our actual and expected RMADs, but the Dirichlet norms suggest that these deviations can generally be accounted for by differences in market share.

There is some store segmentation - there are differences by type of store (observed RMADs across store types were higher than those for different socio-demographic factors between store types), and large households buy more and older people by less. However, these facts were known already. What we were testing here was whether there is actionable segmentation, for instance:

1. Do people differ systematically in their choice of store (or store type) - e.g. do Co-op stores disproportionately attract older buyers? Are national chains patronised by the full-time working housewife more than expected? Our findings suggest not.
2. Do different shopper segments behave differently - e.g. are some types of shopper more or less loyal than average? Again, we did not find any evidence to support this view.

What our results show is that shoppers in different segments behave in similar ways, i.e. patronage and loyalty levels differ very little across socio-demographic segments. This conclusion demands that we re-evaluate loyalty-based customer segmentation schema. Apart from obvious differences (such as large households spend more), there may be fewer behavioural differences than were first believed and therefore fewer points of leverage for those seeking to exploit customer loyalty.
References


