Journal of Marketing and Consumer Research www.iiste.org
ISSN 2422-8451 An International Peer-reviewed Journal
Vol.10, 2015

Consumer Purchase Behaviour in a Frequently bought product Category: Investigation and measure of Brand loyalty.

[1]AKOMOLAFE, ABAYOMI A ,[2]AKINYELE,Atinuke. and [3]OLADIMEJI, Olanrewaju A

[1] Lecturer, Department of Mathematical Sciences ,Ondo State University of Science and Technology, P.M.B 353, Okitipupa,Nigeria (akomolafe01@yahoo.com)

[2]Lecturer, Department of Mathematical Sciences,West African Union University, Republic of Benin, Cotonou. (tinukemii@yahoo.com)

[3] Lecturer, Osun State College Of Technology,P.M.B 1011 Esa- Oke,Osun State

.

ABSTRACT

Past research has predominantly relied on models without incorporating heterogeneity as part of their methodological tools. This research investigates different ways of modeling brand loyalty using a competing risk model that incorporate brand loyalty and study its time dependence.

We introduce previous models by including switch-specific hazard functions, repeat purchases, marketing mix Variables, unobserved heterogeneity and mover- stage type loyalty. An empirical example based on household purchases of disposable products is provided to illustrate the modeling approach.

Results indicate that ignoring heterogeneity will lead to biased inferences concerning time dependence of brand loyalty.

Keywords: Heterogeneity, Mover-Stayer loyalty, Hazard function, and Marketing mix

Introduction

Model Brand loyalty is defined as the time until a consumer switches to another brand for the first time. Duwors and Heunes(2003), developed a new measure of brand loyalty based on event history analysis. This measure is an improvement over previous research as it can lead to either static or time dependent loyalty. However there are several problems with this measure of brand loyalty. Most importantly, heterogeneity is not included into the model which may lead to biased results and spurious state dependence(Heckman 1999). Hence time dependent loyalty may simply be an artifact due to aggregating consumers with heterogeneous purchase probabilities. In addition, only considering time until the first switch will give a deceiving picture of loyalty if brand switching is frequent in a product category.

In addition, any attempt to summarize buying behavior times directly from observed data will be unable to provide accurate estimates of the true, underlying rates of buying behavior. Likewise any, attempt to uncover heterogeneity in buying rates will run into similar problems. The only way to overcome the previous methods and models used in measuring brand loyalty is the incorporation of heterogeneity as exhibited by each and every consumer Vis-a- Vis their buying behavior this will enable us to obtain inferences about differences in buying behavior pattern across consumers and over time.

Model Specification

To understand the overall pattern of these consumers buying behavior we incorporate both brand choice and the timing of purchases simultaneously. The choice set(all brands in the market) is the state space and an event is a purchase occasion. A spall is the period of time between two successive events (the inter purchase time). We use a competing risk model which shows the transition between states (a brand switch) over time, conditional on the history of the process. The proportional hazard model is used tocalibrate our competing – risk model. We assume that the baseline hazard model is weibull distribution that is simple and flexible.

When α= 1, this distribution reduces to an exponential distribution (*no duration dependence*), the hazard functions are increasing (*positive duration dependence*), and for α < 1, there will be negative duration dependence .That is:

$$h_{jk}(t/x) = \alpha t^{\alpha-1} e^{[\sum_i \delta k_{i+} x_j} k_i \beta_j k_i (1)$$

Where: $h_{jk}(t/x)$ is the hazard or transition rate for a switch from brand j to brand x conditional on a vector of covariates.

t = time

α= the parameter of the weibull distribution

δ =The intercept term

$\beta_j k_i$ =Parameter to be estimated

The probability of repeat purchasing a brand is given by the survival probability

1 – F(t) or S(t).

The model allow for multiple brand loyalty, since consumers can have preferences for more than are brand. Also the left censoring or initial conditioning problem is reduced, since all purchases wereincluded. The competing risk model is more appropriate for frequently purchased consumable goods, where a significant amount of switching takes place.

The model is estimated by maximizing the likelihood function:

$$L_i(t) = \prod_{k=1}^{R_i} f_{jk}(t)^{d_{ri}} S_j(t)^{1-d_{ri}} (2)$$

Where k:

K = 1 . . . . . R_i , the number of spells for the i^{th} household.

d_{r_i} = 1 for the r^{th} completed spell [a swich] of the i^{th} household.

for the r^{th}repeat purchase or censored spell and the joint density for the hazard and survivor function for all brands are:

$$S_j(t) = \prod_{j=1}^{M} exp\ [-\int_0^1 h_j(u)du\ ], (3)$$

$$f_{jk}(t) = \prod_{\substack{j=1 \\ j\neq 1}}^{M} h_{jk}(t_{jk}) exp\ [-\int_0^1 h_{jk(u)du}], (4)$$

Where,

J = 1, 2 . . . M, the number of brands, j ≠ k

The first mode we estimate is the competing risk model without marketing mix variables. In the second model we add marketing mix variables to adjust brand loyalty for the effects of marketing mix variables.

Model (3) adds mover- stayer heterogeneity just like spilerman 2000 shows as follows:

$$L_{m-s}\text{ (t/x)} = L_i\text{(t/x)(1-S)}^Z\{L_i\text{ (t/x)(1-S) + S }\}$$

Where:

S = probability that a household is a hard core loyal and

$$Z = \begin{matrix} 1\text{ ,}if\ a\ household\ \ is\ observed\ to\ switch \\ 0\text{ ,}if\ a\ household\ is\ not\ observed\ to\ switch \end{matrix}$$

Consumer specific covariates are incorporated into the hardcore loyalty probability.

More specifically,

$$\text{S = 1 / [1 + exp (}\gamma_0 + \gamma_1\text{ income + }\gamma_2\text{ education)}$$

The fourth model adds “preference” or “intercept”, heterogeneity, where heterogeneity is incorporated as a random effects specification. Heterogeneity is a household specific component that remains constant over time but distributed over the population according to a mixing distribution; g(θ). We specify g(θ) to be a gamma distribution. The gamma distribution has the advantage that it is flexible and combined with the weibull hazard function to achieve a closed form expression(Gonul and Srinivasan 2007), then:

$$L_i\text{(t/x)} = \int_0 \ L_i\text{ (t/x,}\theta\text{) g}\theta\text{ d}\theta\text{(5)}$$

Where:

$$\text{g(q)} = b^a e^{-b_q}\ q^{a-1}\text{/ G(a)}$$

Heckman and singer (2008) show that parameter estimates may be biased and inconsistent due to misspecification of the mixing distribution. Therefore, we also specify the heterogeneity non – parametrically as in the fifth model, using a finite mixture approach and test the fourth model. The non-parametric estimation technique is a discrete approximation of the preference heterogeneity distribution.

Finally, we combine the mover- stayer model with Gamma heterogeneity.

Data

Scanner panel data for disposable Cadbury product was used. Our sample consists of 152 retail outlets with 2675 purchases of the leading company’s product [Bornvita, cookies and biscuit]. Price is the key before coupon price per product adjusted to reflex size differentials. Coupon is a dummy variable indication whether or not a coupon is used.

Results

The results of model comparisons provided in table 1 indicate asymmetry due to the effects of price and coupon across brands.while coupon are significant factors for switching from brand B to A, they are significant for switching from A to B. Brand A and C compete more closely based on marketing mix strategies. To evaluate the results of different models we perform several nested and non- nested tests (see Table 1). The chi- squared test is used for nested models while Akaike information criterionis used to compare the model fit of non-nested models. The smaller number for the A/C indicates a better model fit.

All models that add heterogeneity in preferences(i.e.third, fourth, fifth and sixth model)leads to a considerable improvement in fit, as expected. The fourth model, with preference heterogeneity performs better than the mover – stayer model, indicating that the "partition" of the buying behavior pattern based on preferences yielded a better fit. We find that income is marginally significant in affecting stayer probability.

The estimates of stayer proportion are about 30% in both models. Fourth model provides slightly better fit than fifth model with non- parametric preference heterogeneity. This indicates that there is no problem due to misspecification of the parametric preference heterogeneity distribution. Two mass points were needed to estimate the preference heterogeneity distribution, indicating two different segments. The last model adds mover-stayer loyalty to the fourth model. Besides including differences in individual preferences, this model also distinguishes between hard – core loyal consumers and switches. However there is only a small improvement in fit by adding mover- stayer loyalty to the model, its advantage is computational over preference heterogeneity.

We proceed to compute brand loyalty as the reciprocal of the exit rate. The exit rate for a brand is the summation of the hazard rates, which is the likelihood that a consumer switches to any other brand based on the shape of the empirical exit rate, it is possible to distinguish between increasing,decreasing or static brand loyalties over time. This measure also differs from the preference heterogeneity as the latter is a static measure which is consumer specific rather than brand specific.Brand B has the highest exit rate or the likelihood of losing consumers, while brand A has the lowest exit rate(the highest consumer loyalty).

The inclusion of marketing mix variable leads to a slight decrease in the exit rates for brand A and C, indicating an increase in loyalty for these brands. Brands C gains the most from the marketing mix strategies used. The result of model 1 and 2 without preference heterogeneity display an increasing exit rate over time for all brands, while the exit rates for models with heterogeneity are constant or slightly decreasing. Hence, ignoring differences in consumer preferences leads to different findings concerning duration dependence of brand loyalty.

Our measure of time- dependence loyalty remains virtually stable over time which is consistent with the findings in the literature that for mature frequently purchased goods, consumers are relatively stable for periods of one to two years see Baas et.al(2004).

Conclusion

The exit rate is used as a measure of brand loyalty that can either be static or time dependent. This measure of loyalty is adjusted for the effect of marketing mix variables and heterogeneity in preferences. Our result shows the importance of including consumer heterogeneity while studying the dynamics of brand loyalty. Ignoring this effect may lead to spurious state dependence and biased inference concerning brand loyalty over time.

Our model is a multivariate extension of previous models in the marketing literature. We find out that based on our model there is considerable improvement on parameter estimates as well as the provision of better fit.

References

Bass, Frank M., Moshe M. Givon, Manohar U. Kalwani, David Reibstein and Gordon P. Wright (2004), "An investigation into the Order of the Brand Choice Process," Marketing Science, 3 (Fall), 267-87.

Du Wors, Richard E. Jr. and George H. Haines Jr. (2003), "Event History Analysis Measures of Brand Loyalty," Journal of Marketing Research, Vol. 27,(November), 485-93.

Gönül, Fülsun F. and KannanSrinivasan (2002) "Consumer Purchase Behavior in a Frequently Bought Product Category: Estimation Issues and Managerial Insights from a Hazard Function Model with Heterogeneity, "Journal of the American Statistical Association, Vol. 88, No.424, 1219-27.

Heckman, James J.(1999), "Heterogeneity and State Dependence," in S.Rosened.

Studies, in labor Markets, 91-139, Chicago: University of Chicago press.

Heckman, James J. and Burton singer(2010), "A method for minimizing the impact of Distributional Assumptions in Econometric Models for Duration Data," Econometrica, 52,271-320.

Spilerman, S.(2000), "Extensions of the Mover- Stayer model," American Journal of Sociology, 78, 599-626.

Jamiesan, L.F. and Bass.F.M.,(2009) Adjusting Stated Intension Measures to Predict Trial Purchase of Products: A Comparsion of models and methods. Journal of Marketing Research 26(August), 336 – 345.

Goodhardt,Gerald J., Andrew S.C. Ehienberg and Christopher Chatfield(2004), "The Dirichlet: A comprehensive Model of Buying Behaviour" Journal of the Royal Statistical Society. 147 (5) 621-55.

Table1*: Results of all Models*

Variables	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6
Duration Parameter α	1.34**	1.34**	1.37**	1.49**	1.40**	1.46**
Constant A-> B A-> C B-> A B->C C-> A C-> B	 -3.56** -3.23** -3.51** -3.09** -4.41** -4.17**	 -2.50 1.06 -4.39* 0.28 -1.48 -1.43	 -1.36 2.94* -3.68 -0.29 -1.36 -1.02	 -2.82 -0.01 -4.70** -1.76 -2.09 -1.63	 -4.61** -1.97 -5.98** -2.20 -3.21** -2.12	 -2.15 1.04 -4.11* -1.22 -1.66 -1.23
Price A-> B A-> C B-> A B->C C-> A C-> B		 -0.07 -0.36** 0.02 -0.24** -0.28** -0.19*	 -0.12 -0.45** -0.03 -0.20** -0.25** -0.19**	 -0.03 -0.27* 0.01 -0.13 -0.24* -0.18*	 0.04 -0.19* 0.05 -0.15 -0.21* -0.20**	 -0.06 -0.33** -0.01 -0.15 -0.25** -0.19*
Coupon A-> B A-> C B-> A B->C C-> A C-> B		 0.09 1.18** 1.08** 0.17 1.86** 0.11	 0.14 1.02** 1.16** 0.27 1.70** 0.20	 -0.01 1.11** 1.21** 0.30 1.75** 0.11	 0.02 1.22** 1.09** 0.31* 1.71** 0.16	 -0.02 1.07** 1.20** 0.30 1.72** 0.14
Heterogeneity Location Probability				1.27**	 1.1,-1.5 .57,.43	 0.40**
Mover-stayer Constant Income Education			 0.70 -0.96 0.09			 1.11 -1.13* 0.09
Log-likelihood	-2229.3	-2166.4	-2063.2	-2043.9	-2045.8	-2033.7
AIC	1.672	1.6336	1.5589	1.5424	1.5460	1.5372

** *Significant at .05% level*
* *significant at the .10% level*