

Skiera, Bernd

Working Paper — Digitized Version

A previously unresearched way to gain market share

Manuskripte aus den Instituten für Betriebswirtschaftslehre der Universität Kiel, No. 380

Provided in Cooperation with:

Christian-Albrechts-University of Kiel, Institute of Business Administration

Suggested Citation: Skiera, Bernd (1995) : A previously unresearched way to gain market share, Manuskripte aus den Instituten für Betriebswirtschaftslehre der Universität Kiel, No. 380, Universität Kiel, Institut für Betriebswirtschaftslehre, Kiel

This Version is available at:

<https://hdl.handle.net/10419/181061>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Nr. 380

Bernd Skiera

**A previously unresearched way
to gain market share**

November 1995

Keywords: generalized probit model, choice model, random utility model, error terms

Bernd Skiera, Department of Marketing, University of Kiel, Olshausenstr. 40, 24098 Kiel, Germany, E-mail: skiera@bwl.uni-kiel.d400.de, Phone: ++49-431-880-1541, Fax: ++49-431-880-1166

Abstract

Due to their flexibility in encompassing any structure of the error terms between different brands, generalized probit models evince themselves superior to other random utility models. This superiority implies that the unobservable utility of a brand and hence its market share is a function of the strict utility and the structure of the error terms of all brands in the market. In searching for opportunities to gain market share, the respective research literature has examined only possibilities for influencing the strict utility of a brand. However, substantial market share might be gained also by influencing the structure of the error terms of all brands in the market even when the strict utilities of all brands remain the same.

1 Introduction

Generalized probit models relate the utility function of a brand to a deterministic part, usually called strict utility, and a stochastic part, called error term (McFadden, 1986). The generalized probit model is thus a member of the family of random utility models (Corstjens and Gautschi, 1983). However, in contrast to other kinds of random utility models (e.g. multinomial logit model, independent probit model) it does not impose any restrictions on the structure of the covariance matrix of the different brands' error terms. This flexibility, combined with recent advances in the development of computational estimation methods (Horowitz et al., 1994; Chintagunta, 1992), provides at least two major reasons that the application of the generalized probit model for studying consumer choice behavior is becoming increasingly popular. First, the generalized probit model is appealing theoretically, as it does not suffer from the "independence of irrelevant alternatives" (IIA) property. Second, comparisons between the generalized probit model and other kinds of random utility models indicate that the generalized probit model is superior in terms of predictive validity (Currim, 1982; Chintagunta, 1992).

One important managerial goal of the application of random utility models has been the identification of possibilities to increase the utility - and hence the market share - of a brand. This has been achieved by seeking opportunities to increase the deterministic part of the utility function. Results might have been the identification of relevant marketing mix variables (e.g. Currim, 1982). However, if generalized probit models are indeed more appropriate for describing marketing behavior, this would indicate that the investigation of possibilities to increase the value of the deterministic part of the utility function is only one way to gain market share. Another, previously unresearched way would be to influence the stochastic part; that is, the structure of the error terms. By altering the magnitude of variances and covariances of the different brands' error terms, substantial market share can be gained. Therefore, the aim of this paper is to demonstrate how market share might be gained by influencing the structure of the error terms, and to point out important implications for future research.

In the following section we briefly describe the generalized probit model. Section 3 then demonstrates how gains in market share might be realized by influencing the structure of the error terms. A summary and suggestions for future research are offered in Section 4.

2 The generalized probit model

For the sake of simplicity, we will describe the generalized probit model for the case of two brands where $V(i)$ is the strict utility and $\varepsilon(i)$ is the error term of the i -th brand, and the unobserved utility $U(i)$ can be written as in equation (1):

$$(1) \quad U_i = V_i + \varepsilon_i$$

In this case the probability of choice for the first brand ($P(1)$) is as follows (Daganzo, 1979):

$$(2) \quad P(1) = P[V(1) + \varepsilon(1) > V(2) + \varepsilon(2)] = P[\varepsilon(2) - \varepsilon(1) < V(1) - V(2)]$$

$\varepsilon(2) - \varepsilon(1)$ is normal distributed with zero mean. The variance σ^2 is given by the sum of the variances σ_1^2 and σ_2^2 of $\varepsilon(1)$ and $\varepsilon(2)$ minus twice the covariance $\sigma_{1,2}$ of $\varepsilon(1)$ and $\varepsilon(2)$ (Daganzo, 1979). Therefore, the probability of choosing the first product is:

$$(3) \quad P(1) = \Phi\left(\frac{U(1) - U(2)}{\sigma}\right) = \Phi\left(\frac{U(1) - U(2)}{\sqrt{\sigma_1^2 + \sigma_2^2 - 2 \cdot \sigma_{1,2}}}\right),$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function.

Hence in the generalized probit model, contrast to other kinds of random utility models, the probabilities of choosing one brand depend on the strict utilities and the variances and covariances between the error terms of all brands in the market.

3 Gaining market share by influencing the covariance matrix of the error terms

Assuming, for the reasons outlined above, that market behavior is best described by the generalized probit model, we will demonstrate how market share might be gained by using an approach that has not been investigated up to now. The basic idea of this approach is to influence the structure of the error terms' covariance matrix and gain market share without necessarily altering the value of the strict utility. This approach is thus clearly distinguished from the common approaches in respective literature, which look for possibilities to increase the strict utility of the brand.

Our starting position is the circumstance that has been labeled as case 1 in table 1. The situation: an innovator's brand has a higher strict utility than the brand of an imitator, and the error terms are uncorrelated and have equal variances. For the purpose of illustration assume that

the Marketing-Mix activities taken into account here influence only the error terms' covariance matrix and not the strict utilities of the brands. In this situation, the imitator could choose of these three strategies to increase the market share of his brand:

1. Increase of his own variance (cases 2.1-2.2 in table 1),
2. Increase of the variance of the innovator (cases 3.1-3.2 in table 1),
3. Generate a negative covariance between the innovator's and his own error terms (cases 7.1-7.2 in table 1).

To contrast this, the innovator could choose of the following two strategies:

4. Decrease his own variance or the variance of the imitator (cases 5.1-5.3 in table 1),
5. Generate a positive covariance between the imitator's and his own error terms (cases 6.1-6.2 in table 1).

The results of the application of these strategies are shown in table 1. To allow comparisons with other popular utility models, the results for the independent probit model and the Luce Choice model are also provided. In contrast to the generalized probit model, the independent probit model assumes the error terms to be uncorrelated and to have equal variances (Currim, 1982),¹ whereas the Luce Choice model assumes the error terms to be zero. The latter therefore, is a member of the class of strict utility models (Corstjens and Gautschi, 1983). Because of these restrictions on the structure of the error terms, both models suffer from the IIA property.

Table 1: Effects of different covariance matrices on the market share of two brands

case	brand	strict utility	market share in the			covariance matrix	
			Luce-Choice Model	independent probit model	generalized probit model		
						innovation	imitation
1	innovation imitation	1,00 0,75	0,57 0,43	0,57 0,43	0,57 0,43	1 0	0 1
2.1	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,54 0,46	1 0	0 2
2.2	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,50 0,50	1 0	0 20
3.1	innovation imitation	1,00 0,75	0,57 0,43	0,54 0,46	0,54 0,46	2 0	0 2
3.2	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,50 0,50	20 0	0 2
4.1	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,55 0,45	0,5 0	0 2
4.2	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,55 0,45	0,1 0	0 2
5.1	innovation imitation	1,00 0,75	0,57 0,43	n.d. n.d.	0,59 0,41	1 0	0 0,5
5.2	innovation imitation	1,00 0,75	0,57 0,43	0,64 0,36	0,64 0,36	0,5 0	0 0,5
5.3	innovation imitation	1,00 0,75	0,57 0,43	1,00 0,00	1,00 0,00	0,05 0	0 0,05
6.1	innovation imitation	1,00 0,75	0,57 0,43	0,57 0,43	0,60 0,40	1 0,5	0,5 1
6.2	innovation imitation	1,00 0,75	0,57 0,43	0,57* 0,43*	1,00 0,00	1 0,999	0,999 1
7.1	innovation imitation	1,00 0,75	0,57 0,43	0,57* 0,43*	0,56 0,44	1 -0,5	-0,5 1
7.2	innovation imitation	1,00 0,75	0,57 0,43	0,57* 0,43*	0,55 0,45	1 -1	-1 1

n.d.: independent probit model is not defined for the corresponding covariance matrix

*: covariances are not taken into account in the independent probit model

In cases where the imitator increases own variance (strategy 1), his market share goes up from 43% (case 1 in table 1) to 50% (case 2.2). Similar results are obtained by following strategy 2, in which the variance of the innovator is increased (case 3.2). When a negative covariance between the error terms of the two brands is generated, market share still goes up from 43% to 45% (case 7.2). Furthermore, it is interesting to observe that the innovator himself has little possibility to react to an increase in the imitator's variance by influencing his own variance. Increasing his variance (cases 3.1-3.2) as well as decreasing his variance (cases 4.1-4.2) leads to a loss in market share. In contrast to this however, the innovator is able to gain substantial market share by following strategy 4 - decreasing the variances of the error terms of both brands (cases 5.1-5.3) - as well as by following strategy 5, which generates a positive correlation between the error terms (cases 6.1-6.2).

This example demonstrates that gains in market share for a brand can be achieved by influencing the covariance matrix of the error terms, even if the strict utilities for all brands remain the same. To the best of our knowledge, this approach has not been outlined in previous literature. Hence, the implications of such a possibility to gain market share by the use of Marketing-Mix instruments have not yet been analyzed. We therefore wish to illustrate some possible opportunities of doing so by using the Marketing-Mix instrument "advertising" as an example. Faced with the starting position in table 1, where the imitator has a lower strict utility than the innovator, the imitator could increase the variance of his brand's error term by using advertising messages that give very little information but underline some fascinating aspects of the brand. On the other side, the innovator should try to keep the variance of both brands' error terms as low as possible. This could be attempted by striving for advertising messages that give information on the features of both brands. Furthermore, the innovator should try to generate positive correlations between the error terms. This might be realized by means of an advertising message emphasizing the same features of the brand that the advertising message of the imitator does.

4 Conclusions

Comparisons between various types of random utility models have demonstrated the generalized probit model to be superior (Currim, 1982; Chintagunta, 1992). The reason for this is that the generalized probit model has the flexibility to encompass any structure of the error terms. This superiority implies that the unobservable utility of a brand, and hence, its market share are functions of the strict utility and structure of the error terms of all brands in the market. However, in searching for opportunities to gain market share, previous literature has only examined

possibilities derived from influencing the strict utility of a brand. Possibilities derived from influencing the structure of the error terms have been completely overlooked. The example outlined above indicates, however, that variation of the error terms' structure can result in substantial market share gains. Future research should thus concentrate more strongly on possibilities for influencing the covariance matrix of the error terms. Valuable results might be obtained through analysis of different advertising messages and different information acquisition strategies.

Literature

- Chintagunta, P.K. (1992), Estimating a multinomial probit model of brand choice using the method of simulated moments, *Marketing Science*, 11, 386-407
- Corstjens, M.L. and Gautschi, D.A. (1983), Formal Choice Models in Marketing, *Marketing Science*, 2, 19-56
- Currim, I.S. (1982), Predictive Testing of Consumer Choice Models not Subject to Independence of Irrelevant Alternatives, *Journal of Marketing Research*, 19, 208-222
- Daganzo, C. (1979), *Multinomial Probit, The Theory and Its Application to Demand Forecasting*, New York et al.: Academic Press
- Horowitz, J.L. et al. (1994), Advances in Random Utility Models. Report of the Workshop on Advances in Random Utility Models. Duke Invitational Symposium on Choice Modeling Behavior, *Marketing Letters*, 5, 311-322
- McFadden, D. (1986), The Choice Theory Approach to Market Research, *Marketing Science*, 5, 275-297

Acknowledgments

The author wishes to thank Sönke Albers for his many helpful comments and suggestions, and Vithala Rao for a fertile discussion of the basic idea for this paper.

Notes

- ¹ We would like to point out that some authors (e.g. Chintagunta, 1992) distinguish between two kinds of independent probit models: the Standard Independent Probit Model in which covariances are zero and variances are constrained to 1, and the Independent Probit Model in which covariances are zero but variances are allowed to be different for different brands. We do not follow this distinction because it offers only limited additional insight. Furthermore, note that a logit model would show results fairly similar to the results of the independent probit model.