

Advertising Response Models for Marketing-OM Interface Research

Qinglong Gou¹, Xiaohang Yue^{2*}, Juan Zhang¹ and Juzhi Zhang¹

¹School of Management, University of Science and Technology of China, Hefei, Anhui, 230026, P.R. China

²School of Business, University of Wisconsin–Milwaukee, Milwaukee, WI 53201-0413, USA

Research on the interface between marketing and operation management (OM) is an emerging area. Generally speaking, marketing is the creation of customer demand and operations management is the supply and fulfillment of customer demand [1]. In practice, managing the interface between the marketing and operations is a very challenging task because these two areas are often in conflict. For example, it is better to increase product diversity from the marketing point of view; while a manufacture wants to reduce the product variations [2]. Since conflicts between the two areas often lead to production inefficiencies and unsatisfied customers, co-ordination between marketing and operations is critical for a firm to be successful.

In Marketing-OM interface, advertising expenditure and pricing are two essential elements. Although the topics of Marketing-OM interface research vary significantly, advertising response models are the basis for decision makings. This purpose of this paper is to introduce how to choose a suitable advertising response model for marketing-OM interface researches.

Generally, when authors choose their advertising models for their Marketing-OM interface researches, the following three factors should be carefully considered: (i) to choose an aggregate model or an individual model, (ii) to choose a static or a dynamic advertising response model, (iii) to verify the empirical basis of the model.

Aggregate Models v.s. Individual Models

Typically, there are two types of advertising response models: the aggregate and individual models. Aggregate advertising response models characterize the effects of various marketing variables on the product demand in a market level, whereas the individual advertising response models are usually used to depict the individual customer behavior with advertising efforts taking into account.

Aggregate advertising response models usually can be classified into priori models and econometric models. Commonly, econometric models could have a linear [3-7] or non-linear forms [8-12]. Piori advertising models have two typical forms. One is Vidale-Wolfe model [13] and its modifications [14-20], and the other is Nerlove-Arrow model [21] and its extensions [22-25]. Recently, a new priori advertising model based on Lotka-Volterra model was proposed by Wang et al. [26].

The individual advertising response models are usually based on consumer's utility and surplus [27-29]. Specifically, such models assume that: (i) a consumer has a certain utility when he/she consumes a product, (ii) whether a consumer buys a product or not depends on his surplus, and (iii) consumers' utility for a certain product are heterogeneously according to certain probability distribution. Combining the above three assumptions, the sales of a product can be a certain integration of the probability function.

Static v.s. Dynamic Advertising Response Models

Advertising response models are in static and dynamic forms. In static models, the sales is an direct function of marketing variables such as price and advertising efforts or budgets. Examples of such models

include Berger [30], Huang and Li [31], Huang, Li, and Mahajan [32], Yue et al. [33], and Xie and Wei [34]. In dynamic models, market state variables such as sales, market shares and goodwill are changing dynamically by the advertising efforts and are expressed by means of differential equations. Main dynamic advertising models include Nerlove-Arrow model [35], Vidale-Wolfe model, Sethi advertising model [36] and their modifications.

Although dynamic models can characterize the advertising carry-over effect well, authors may have to face the difficulty in obtaining a close-loop solution for decision models. Therefore, utilizing a static advertising response model in a two-stage framework to analyze the system dynamicity is a substitutable choice and is increasingly adopted by researchers [37,38].

Empirical Basis of Advertising Response Models

When authors utilize or choose an advertising response model, its empirical basis should be carefully considered. An advertising response model without empirical evidence supporting makes the whole study doubtful.

It is difficult to introduce an advertising response model satisfying all the characteristics in empirical studies. For instance, summarizing previous advertising empirical studies, Little [39] once proposed five criteria and showed that the most cited models such as Vidale-Wolfe model, Nerlove-Arrow model, Lanchester model and their modifications would not satisfy the five criteria properly. Based on the consumer's population dynamics, Wang et al. [26] introduces an advertising response model which fits Little's five criteria well, but its mathematical complexity makes it impossible to be widely used in marketing-OM interface research.

Therefore, recognition of the advantages and disadvantages of each advertising response model is important to choose a suitable model for marketing-OM interface research. A simple model which can grasp the main characters of the considered problem should always be advocated. Also, reviewers should not be overcritical to require the advertising response model of a paper satisfying too much empirical characteristics.

Suggestions for Choosing Advertising Response Models

Advertising response models are the basis of marketing-OM interface researches. An advertising response model with a support

*Corresponding author: Xiaohang Yue, School of Business, University of Wisconsin–Milwaukee, Milwaukee, WI 53201-0413, USA, E-mail: xyue@uwm.edu

Received July 12, 2012; Accepted July 14, 2012; Published July 17, 2012

Citation: Gou Q, Yue X, Zhang J, Zhang J (2012) Advertising Response Models for Marketing-OM Interface Research. *Ind Eng Manage* 1:e107. doi:10.4172/2169-0316.1000e107

Copyright: © 2012 Gou Q, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

of empirical evidences can ensure the correctness of conclusions from marketing-OM interface decision models, whereas a simple form of the advertising response model would reduce the research complexity mathematically. Since a simple model may not satisfy all the advertising characters from empirical studies, authors should make a balance between the empirical evidence and mathematical complexity when they model advertising responses.

Detailed suggestions for choosing advertising response models include: (i) aggregate response models should be firstly considered to reduce the mathematical complexity of a decision making process; (ii) Nerlove-Arrow model and/or Sethi's advertising model can be a preferential choice to formulate the advertising carry-over effect; (iii) authors also would utilize static models in a two or multiple stages framework to formulate a dynamic system; (iv) individual response models based on consumer utility and surplus are powerful in modeling most advertising effects, they are good choices when there are less than three decision variables in the research problems.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grand No. 70901068), the Funds for International Cooperation and Exchange of the National Natural Science Foundation of China (Grant No. 71110107024).

References

1. Ho TH, Tang CS (2004) Introduction to the Special Issue on Marketing and Operations Management Interfaces and Coordination. *Management Science* 50: 429-430.
2. Shapiro BP (1977) Can marketing and manufacturing co-exist? *Harvard Business Review*.
3. Bass FM, Clarke DG (1972) Testing Distributed Lag Models of Advertising Effect. *J Mark Res* 9: 298-308.
4. Bass FM, Leone RP (1983) Temporal aggregation, the data interval bias, and empirical estimation of bimonthly relations from annual data. *Management Science* 29: 1-11.
5. Greuner M, Kamerschen D, Klein P (2000) The competitive effects of advertising in the US automobile industry, 1970-94. *International Journal of the Economics of Business* 7: 245-261.
6. Telang R, Boatwright P, Mukhopadhyay T (2004) A mixture model for internet search engine visits. *J Mark Res* 41: 206-214.
7. Yao S, Mela CF (2011) A Dynamic Model of Sponsored Search Advertising. *Marketing Science* 30: 447-468.
8. Lambin JJ (1972) A Computer On-Line Marketing Mix Model. *J Mark Res* 9: 119.
9. Clarke DG (1973) Sales-Advertising Cross-Elasticities and Advertising Competition. *J Mark Res* 10: 250-261.
10. Vakratsas D, Feinberg FM, Bass FM, Kalyanaram G (2004) The shape of advertising response functions revisited: a model of dynamic probabilistic thresholds. *Marketing Science* 23: 109-119.
11. Ghose A, Yang S (2009) An empirical analysis of search engine advertising: sponsored search in electronic markets. *Management Science* 55: 1605-1622.
12. Yang S, Ghose A (2010) Analyzing the relationship between organic and sponsored search advertising: positive, negative or zero interdependence? *Marketing Science* 29: 602-623.
13. Vidale ML, Wolfe HB (1957) An operations research study of sales response to advertising. *Operations Research* 5: 370-381.
14. Kimball GE (1957) Some industrial applications of military operations research methods. *Operations Research* 5: 201-204.
15. Ozga SA (1960) Imperfect markets through lack of knowledge. *The Quarterly Journal of Economics* 74: 29-52.
16. Sethi SP (1983) Deterministic and stochastic optimization of a dynamic advertising model. *Optimal Control Applications and Methods* 4: 179-184.
17. Sorger G (1989) Competitive dynamic advertising: A modification of the case game. *J Econ Dyn Control* 13: 55-80.
18. Wang Q, Wu Z (2001) A duopolistic model of dynamic competitive advertising. *Eur J Oper Res* 128: 213-226.
19. Erickson GM (2009) Advertising competition in a dynamic oligopoly with multiple brands. *Operations Research*.
20. Mesak HI, Ellis TS (2009) On the superiority of pulsing under a concave advertising market potential function. *Eur J Oper Res* 194: 608-627.
21. Nerlove M, Arrow KJ (1962) Optimal advertising policy under dynamic conditions. *Economica* 29: 129-142.
22. Jørgensen S, Sigue SP, Zaccour G (2000) Dynamic cooperative advertising in a channel. *Journal of Retailing* 76: 71-92.
23. Jørgensen S, Taboubi S, Zaccour G (2001) Cooperative Advertising in a Marketing Channel. *J Optim Theory Appl* 110: 145-158.
24. Bruce NI (2008) Pooling and dynamic forgetting effects in multi theme advertising: Tracking the advertising sales relationship with particle filters. *Marketing Science* 27: 659-673.
25. Zhang J, Gou Q, Liang L, Huang Z (2012) Supply chain coordination through cooperative advertising with reference price effect. *Omega* 1-9.
26. Wang M, Gou Q, Wu C, Liang L (2012) An aggregate advertising response model based on consumer population dynamics. *Int J Applied Management Science* x: 1-17.
27. Lal R, Narasimhan C (1996) The inverse relationship between manufacturer and retailer margins: A theory. *Marketing Science* 15: 132-151.
28. Bloch F, Manceau D (1999) Persuasive advertising in Hotelling's model of product differentiation. *International Journal of Industrial Organization* 17: 557-574.
29. Shaffer G, Zettelmeyer F (2004) Advertising in a Distribution Channel. *Marketing Science* 23: 619-628.
30. Berger PD (1973) Statistical analysis of cooperative advertising models. *Operational Research Quarterly* 24: 207-216.
31. Huang Z, Li SX (2001) Co-op advertising models in manufacturer-retailer supply chains: A game theory approach. *Eur J Oper Res* 135: 527-544.
32. Huang Z, Li SX, Mahajan V (2002) An Analysis of Manufacturer-Retailer Supply Chain Coordination in Cooperative Advertising. *Decision Sciences* 33: 469-494.
33. Yue J, Austin J, Wang MC, Huang Z (2006) Coordination of cooperative advertising in a two-level supply chain when manufacturer offers discount. *Eur J Oper Res* 168: 65-85.
34. Xie J, Wei JC (2009) Coordinating advertising and pricing in a manufacturer-retailer channel. *Eur J Oper Res* 197: 785-791.
35. Fudenberg D, Tirole J (1984) The Fat-Cat Effect, the Puppy-Dog Ploy, and the Lean and Hungry Look. *Am Econ Rev* 74: 361-366.
36. Bagwell K, Ramey G (1988) Advertising and Limit Pricing. *Rand J Econ* 19: 59-71.
37. Chintagunta PK, Vilcassim NJ (1992) An empirical investigation of advertising strategies in a dynamic duopoly. *Management Science* 38: 1230-1244.
38. Esteves RB (2009) Customer Poaching and advertising. *J Ind Econ* 57: 112-146.
39. Little JDC (1979) Aggregate advertising models: The state of the art. *Operations Research* 27: 629-667.