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MODELING COMPETITIVE MARKETING BEHAVIOR:A CRITICAL REVIEW OF THE LITERATURE

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Abstract

The purpose of this review is to focus on models of market mechanisms that contain a sales response function and competitive reaction functions. Understanding such models can lead to improvements in the Marketing productivity of individual firms, as demonstrated by Parsons and Bass (1971), Hanssens et al. (2001). This paper discusses major theoretical developments in modeling competitive Marketing behavior with respect to several variables.

We begin by discussing the work of Lambin, Naert and Bultez (1975) (LNB), who have generalized the Dorfman-Steiner theorem to the case of an oligopoly with multiple competitive reactions and expansible industry demand. Next, we analyze the extended LBN model by Hanssens (1980) which incorporates the phenomena of the level of one marketing instrument affecting, or being affected by, levels of other marketing instruments within the same firm into a generalized reaction matrix. Finally, the important issues of modeling asymmetric brand competition, not introduced in the precedent frameworks, as well as the prediction of competitive marketing behavior will be introduced.

Keywords

Competitive Marketing Behavior; Modeling; Prediction; Decision Models

Introduction

Marketing managers regularly face the problem of selecting the Marketing mix that will optimally accomplish their goals within the constraints in which they operate. This becomes known as the Marketing programming problem (Kotler, 1971). The development and implementation of marketing decision models will result in better Marketing decisions. These models specify how current Marketing actions will produce current or future Marketing results. The purpose of this review is to focus on models of market mechanisms that contain a sales response function and competitive reaction functions – market response models. According to Hanssens et al. (2005), these models are intended to help scholars and managers understand how consumers individually and collectively respond to marketing activities, and how competitors interact. Understanding such models can lead to improvements in the Marketing productivity of individual firms, as demonstrated by Parsons and Bass (1971). Lambin (1970, 1976), Metwally (1978) and Hanssens et al. (2001) have pointed out that a tendency exists in saturated markets (in these markets there are not primary demand effects, that is, the industry sales is stable and doesn't respond to the mix of the firms) for the Marketing efforts of competitors to cancel each other out. With competitive reaction an escalation of marketing effort can take place.

This study discusses major theoretical developments in modeling competitive Marketing behavior with respect to several variables.

The important work by Lambin, Naert and Bultez (1975) (LNB), who have generalized the Dorfman-Steiner (1954) theorem to the case of an oligopoly with multiple competitive reactions and expandable industry demand, will be introduced.

There are many studies analyzing competitive Marketing behavior (Leeflang and Wittink, 1992, 1996, 2000, 2001; Steenkamp et al., 2005) and some key ones will be analyzed by applying the LNB framework to them. The extended LNB model by Hanssens (1980) incorporate the phenomena of the level of one Marketing instrument affecting, or being affected by, levels of other Marketing instruments within the same firm into a generalized reaction matrix, will be introduced. Carpenter, Cooper, Hanssens and Midgley (1988) present methods for modeling asymmetric brand competition, an important issue not modeled in the precedent frameworks. Finally, Gatignon, Anderson and Helsen (1989), Alsem, Leeflang and Reuyl (1989) and Leeflang and Wittink (2001) showed that the firms' marketing instruments might also depend on the predicted values of the competitors' marketing instruments. As noted by Armstrong, Brodie and McIntyre (1987, p.361) most of the research on the market share forecasting has assumed that these actions are known. The classical hypothesis postulated is that the competitor behavior is known and assumed to be the same in the future.

Optimal Marketing Decision Models

The Dorfman-Steiner Theorem

We consider a firm which make three kinds of choice: the price of its product, P, the amount of its advertising expenditures, A, and the level of the quality (we mean any aspect of a product, including the services included in the contract of sales, which influences the demand curve) of its product, *Q*. The relationship between the quantity a firm can sell per unit of time, *q* and *P*, *A*, and Q can be denoted by the formula *q=f(P, A, Q)*. We assume that *q=f(P, A, Q)* is continuous and differentiable.

Dorfman and Steiner (1954) hereafter DS, developed a solution for a demand function with price, advertising and product quality as decision variables, thus showing conditions for an optimal Marketing mix. They found that if the selection of the levels for various Marketing instruments are independent decisions, the conditions for the optimal Marketing mix of price, advertising expenditures and product quality expenditures are that the negative of the price elasticity equals the marginal revenue product of advertising equals the product quality elasticity times the ratio of price to unit cost, *C*, that is,

$$-\varepsilon_P = P\frac{\partial q}{\partial A} = \varepsilon_Q \frac{P}{C} \qquad (1)$$

While this relation doesn't directly specify the optimal Marketing mix, it can be used to evaluate whether or not a brand is operating efficiently. This assessment may be easier to make if we write the first part of (1) as

$$\frac{A^*}{R} = -\frac{\varepsilon_A}{\varepsilon_P} \qquad (2)$$

From equation (1), $-\varepsilon_P = P\frac{\partial q}{\partial A}$, then $-\varepsilon_P \frac{A}{q} = P\frac{\partial q}{\partial A}\frac{q}{A} \Leftrightarrow \frac{A}{qP} = -\frac{\varepsilon_A}{\varepsilon_P} \Leftrightarrow \frac{A}{R} = -\frac{\varepsilon_A}{\varepsilon_P}$. Where $\frac{A^*}{R}$ is the ratio of advertising to sales revenue. The optimal advertising-revenue ratio is a constant.

Dorfman and Steinar (1954) have given the necessary conditions for maximum net revenue. Firstly, price and advertising expenditures are the only variables affecting the demand for the product. Secondly, current advertising expenditures don't affect the future demand for the product: the advertising hasn't dynamic or carryover effects. Thirdly, the decision-maker is a monopolist who can determine both price and advertising expenditures.

The DS theorem, especially equation (2) is often used to evaluate whether a brand is operating efficiently. Is our Marketing mix optimal? Are we over-advertising? Do departures from optimal Marketing mix levels really matter?

Applications of the DS theorem have shown wide variations around optimal spending levels, Lambin (1976), Corstjens and Doyle (1981). There are at least two reasons why a branded consumer good might be over-advertised (Aaker and Carman, 1982). First, organizational considerations favor overspending. Most managers are risk averse. They are reluctant to reduce advertising because of the potential adverse effects for sales and market share. Second, in markets that are highly competitive, managers respond to competitive pressure by increasing advertising expenditures.

Bultez and Naert (1979, 1988), Magat, McCann and Morey (1986, 1988) have explored the issue of whether lag structure matters in optimizing advertising expenditures and if so, when. Bultez and Naert (1979) found that while misspecification in the lag structure impacted the optimal advertising budget, profits were not very sensitive to such errors. Magat, McCann and Morey (1986) investigated whether Naert and Bultez's result was universally true or whether it depended on the characteristics of the product and the market analyzed. They determined for any given error in "optimal" advertising, that profits were less sensitive to misspecification, the shorter the duration of advertising effect, the greater the advertising elasticity, the less price-elastic the demand, the lower the unit cost of product and the lower the firm's discount rate.

The Nerlove-Arrow's (1962) Extension: The Introduction of Dynamics

The DS model is extended by Nerlove and Arrow (1962) to cover the situation in which present advertising expenditures affect the future demand for the product, i.e. to take into account the dynamics of advertising. They modeled advertising expenditures like a stock of "goodwill", A_t , which they suppose summarize the effects of current and past advertising outlays on demand. The price of a unit of goodwill, e.g. £1 so, one Pound of current advertising expenditures increases goodwill by a like amount. On the other hand, one Pound spent some time ago should contribute less. One possible way of representing this lesser contribution is to say that goodwill, like many other capital goods, depreciate, and that depreciation occurs at a constant proportional rate δ,

$$\frac{dA_t}{dt} = A - \delta A_t \tag{3}$$

Where, A is current advertising outlay. Equation (3) states that the net investment in goodwill is the difference between the gross investment (current advertising outlay) and the depreciation of the stock of goodwill. If the discount rate,δ , is fixed, then the optimal policy can be found by applying the calculus of variations to the following problem:

$$Max\int_0^\infty e^{-\alpha t}\left[(P-C)q - A\right]dt \tag{4}$$

Subject to $\frac{dA_t}{dt} = A - \delta A_t$, with $A_{(t=0)}$ known and C representing unit cost.

Nerlove and Arrow (1962) assume that the firm attempts to maximize the present value of the stream of revenues net of both production expenses and advertising policies over time. Because price appears only in the integrand, the optimal price can be found first while holding goodwill constant. Then, using optimal price, optimal advertising can be found as

$$\frac{A^*}{R} = -\frac{\delta}{(\alpha+\delta)} \cdot \frac{\varepsilon_{A_t}}{\varepsilon_P} \tag{5}$$

Where ε_{A_t} is the elasticity of demand with respect to "goodwill". This is a generalization of the DS condition. The DS condition is the special case in which the discount rate, α , is zero and the depreciation rate, δ , is 1 (and consequently $A_t = A$). Picconi and Olson (1978) used this ratio in determining the optimal proportion of sales dollars spent on advertising in the case of a branded beverage.

The Lambin, Naert and Bultez (LNB) (1975) Model: Oligopolistic Marketing Competition

Lambin, Naert and Bultez (1975) have generalized the DS theorem to the case of an oligopoly with multiple reactions and expandable industry demand. The competitive reaction is taken explicitly into account. It is assumed that competitors will react with the same Marketing instrument as the one, which causes their reaction, that is, they react to a change in prices by a change in price, to a change in advertising by a change in advertising. This kind of reaction is identified as simple competitive reaction case. A more realistic case also taken by the authors is the multiple competitive reactions: a competitor may react to a change in price not just by changing his price, but also by changing his advertising, and possibly other marketing instruments as well. Before we go ahead, some notation is needed for clarification purposes.

LNB derived optimality conditions in terms of the vector of total sales elasticities, $E_{q,u}$. We will show how they decompose $E_{q,u}$ in its components related to industry sales or primary demand effects and market share effects.

Let be $u' = (u_1, u_2, \cdots, u_n)$ the firm's decision or marketing mix vector, where, $u_1 = p = price$, $u_2 = a =$ advertising, $u_3 = x = \text{product quality index}$, and $U' = (U_1, U_2, \cdots, U_n)$ the competitors' decision vector (the model treats a firm's competition as a whole, so the market is defined as the subject firm plus all other firms), where, $U_1 = P = \text{average price of competitors}$, $U_2 = A =$ advertising expenditures of competitors, $U_3 = X = \text{average product quality index of competitors}$,

$$u^{*'} = (u_1^*, u_2^*, \cdots, u_n^*),\ u_i^* = \frac{u_i}{U_i}, u^{0'} = (u_1^0, u_2^0, \cdots, u_n^0),\ u_i^0 = \frac{u_i}{u_i + U_i},$$

$U^{0'} = (U_1^0, U_2^0, \cdots, U_n^0),\ U_i^0 = \frac{U_i}{u_i + U_i}$ for $i = 1, 2, \cdots, n$, the relative and share variables.

The environmental variables, $Z' = (Z_1, Z_2, \cdots, Z_n)$, where, for example, $Z_1 = \text{per capita income}$, $Z_2 = \text{population size}$.

The demand variables, where, q = firm sales, Q = industry sales or primary demand, $Q_C = Q - q =$ competitors' sales, m = firm market share.

The demand equations, where, $q = q_i(u, U, Z)$, $Q = Q_T(u, U, Z)$, $m = m_i(u, U)$ or $m = m_i(u^*)$ or $m = m_i(u_i^0)$.

Cost and profit variables, where, mc = marginal cost, p – mc = w = gross margin, $\frac{p - mc}{p} = w^* =$ percentage of gross margin, $C = C_i(q, x)$, cost function.

Vector of demand elasticities, $E'_{y,x} = (\eta_{y,x_1}, \eta_{y,x_2}, \cdots, \eta_{y,x_n})$, where,

$\eta_{y,x_i} = \frac{\partial y}{\partial x_i} \cdot \frac{x_i}{y}$, $y \in \{q, Q_C, m, m_i, Q_T\}$, $x \in \{u, U, u^*, u^0\}$, and $E_{m_i} = \begin{pmatrix} E_{m_i,u} \\ E_{m_i,U} \end{pmatrix}$, $E_{Q_T} = \begin{pmatrix} E_{Q_T,u} \\ E_{Q_T,U} \end{pmatrix}$,

$E_{Q_T,u} =$ Vector of primary demand elasticities of the marketing variables of the firm, $E_{Q_T,U} =$ Vector of primary demand elasticities of the marketing variables of its competitors, $E_{m_i,u} =$ Vector of market shares elasticities of the marketing variables of the firm, $E_{m_i,U} =$ Vector of market shares elasticities of the marketing variables of its competitors, R = matrix of reactions elasticities (the effects of firm's decision variables on competitive decisions),

that is, $R = \begin{pmatrix} \rho_{U_1,u_1} & \rho_{U_2,u_1} & \cdots & \rho_{U_n,u_1} \\ \rho_{U_1,u_2} & \rho_{U_2,u_2} & \cdots & \rho_{U_n,u_2} \\ \vdots & & \ddots & \\ \rho_{U_1,u_n} & \rho_{U_2,u_n} & \cdots & \rho_{U_n,u_n} \end{pmatrix}$, where $\rho_{U_j,u_i} = \frac{\partial U_j}{\partial u_i} \cdot \frac{u_i}{U_j}$.

Some elasticities may be instantaneous, while others may occur after a considerable time lag. So ρ_{U_k,u_k} could be defined as $\frac{\partial U_{k,t}}{\partial u_{k,t-1}} \cdot \frac{u_{k,t-1}}{U_{k,t}}$, whereas $\rho_{U_l,u_l} = \frac{\partial U_{l,t}}{\partial u_{l,t}} \cdot \frac{u_{l,t}}{U_{l,t}}$.

The main diagonal elements or direct reaction elements represent simple competitive reaction elasticities and the off-diagonal elements, multiple competitive reaction or indirect reaction elements.

The optimality conditions:

If we take as firm's profit function,

$$\Pi = q(p - C_i(q, x)) - a \tag{6}$$

Then, the optimality conditions can be obtained by setting the derivative of Π with respect to each of the decision variables equal to zero. If $u' = (p, a, x)$, then

$$\frac{\partial \Pi}{\partial u} = \frac{\partial q}{\partial u}(p - c) + q\left(\frac{\partial p}{\partial u} - \frac{\partial C_i}{\partial u} - \frac{\partial C_i}{\partial q} \cdot \frac{\partial q}{\partial u}\right) - \frac{\partial a}{\partial u} = 0 \tag{7}$$

Let D_u be a diagonal matrix of the elements of vector u, here $D_u = \begin{pmatrix} p & 0 & 0 \\ 0 & a & 0 \\ 0 & 0 & x \end{pmatrix}$, and if we pre-multiply (7) by $\frac{D_u}{q}$, then

$$(p - C - q\frac{\partial C_i}{\partial q}) \cdot \frac{D_u}{q} \cdot \frac{\partial q}{\partial u} + D_u \frac{\partial p}{\partial u} - D_u \frac{\partial C_i}{\partial u} - D_u \frac{\partial a}{\partial u} = 0 \tag{8}$$

with $mc = C + q \cdot \frac{\partial C_i}{\partial q}$, and observing that $\frac{D_u}{q} \cdot \frac{\partial q}{\partial u} = E_{q,u}$, the following optimality condition is obtained:

$$E_{q,u} \cdot (p - mc) + \mathrm{I}\begin{pmatrix} p & -\frac{a}{q} & -x\frac{\partial C_i}{\partial x} \end{pmatrix}' = 0 \tag{9}$$

where, I is the identity matrix. From equation (9) one can deduce the DS theorem as

$$-\eta_{q,p} = \frac{pq}{a} \cdot \eta_{q,a} = \frac{p}{x\frac{\partial C_i}{\partial x}} \cdot \eta_{q,x} = \frac{1}{w^*} \tag{10}$$

It states that at optimality, the marginal revenue must equal marginal cost for each marketing instrument. We can easily derive the optimal values for the decision variables. In vector notation, we obtain

$$u = \left(\frac{mc}{1+\eta_{q,p}}\right) \cdot D_{E_{q,u}} \begin{pmatrix} 1 & -q & -\frac{1}{\frac{\partial C_i}{\partial x}} \end{pmatrix}', \text{ where } D_{E_{q,u}} = \begin{pmatrix} \frac{p}{q} \cdot \frac{\partial q}{\partial p} & 0 & 0 \\ 0 & \frac{a}{q} \cdot \frac{\partial q}{\partial a} & 0 \\ 0 & 0 & \frac{x}{q} \cdot \frac{\partial q}{\partial x} \end{pmatrix}.$$

The vector $E_{q,u}$ of total sales elasticities can be decomposed into various elements in the case of an oligopoly. We can distinguish between primary demand effects or industry sales effects and market share effects that can include primary sales effects and competitive effects. Following Hanssens, Parsons and Schultz (2001), the Marketing effects can be decomposed in primary demand effects, when the effect of a brand's marketing activities is to increase its own sales and those of its competitors, and market share effects, which can be decomposed into, primary sales effects (increase its own sales without affecting competitors' sales), and competitive effects (increase its own sales and to decrease those of its competitors). The theorem proposed by LNB, traces the links between total sales elasticities, industry demand, market share and competitive reaction elasticities.

***Theorem*:**
"The vector of elasticities of company sales with respect to its decision variables is equal to a matrix partitioned into an identity matrix and the matrix of competitive reaction elasticities post multiplied by the sum of the vectors of industry sales and market share elasticities", that is,

$$E_{q,u} = (\mathrm{I} \quad | \quad R) \cdot (E_{Q_T} + E_{m_i}) \tag{11}$$

***Proof*:**
Company sales can be written as industry sales times market shares, $q = Q \cdot m$, $q = Q_T(u,U,Z) \cdot m_i(u,U)$.The derivative of q with respect to the decision vector u is $\frac{\partial q}{\partial u} = m \cdot \frac{\partial Q_T}{\partial u} + m \cdot \frac{\partial U}{\partial u} \cdot \frac{\partial Q_T}{\partial U} + Q \cdot \frac{\partial m_i}{\partial u} + Q \cdot \frac{\partial U}{\partial u} \cdot \frac{\partial m_i}{\partial U}$, where, $\frac{\partial U}{\partial u} = \begin{pmatrix} \frac{\partial U_1}{\partial u} & \cdots & \frac{\partial U_n}{\partial u} \end{pmatrix}$ and $\frac{\partial U_i}{\partial u} = \begin{pmatrix} \frac{\partial U_i}{\partial u_1} & \cdots & \frac{\partial U_i}{\partial u_n} \end{pmatrix}'$.

Pre-multiplying by $\frac{D_u}{q}$, we obtain

$\frac{D_u}{q} \cdot \frac{\partial q}{\partial u} = \frac{D_u}{Q} \cdot \frac{\partial Q_T}{\partial u} + \frac{D_u}{Q} \cdot \frac{\partial U}{\partial u} \cdot \frac{\partial Q_T}{\partial U} + \frac{1}{m} \cdot D_u \cdot \frac{\partial m_i}{\partial u} + \frac{1}{m} \cdot D_u \cdot \frac{\partial U}{\partial u} \cdot \frac{\partial m_i}{\partial U}$ which reduces to

$$E_{q,u} = E_{Q_T,u} + R \cdot E_{Q_T,U} + E_{m_i,u} + R \cdot E_{m_i,U} \quad (12) \quad \Leftrightarrow$$

$$E_{q,u} = (\mathrm{I} \;\; | \;\; R) \cdot \left(E_{Q_T} + E_{m_i}\right) \quad \text{Q.E.D.}$$

The optimality conditions are then obtained by substituting the elements on the right-hand side of equation (11) for the elements of $E_{q,u}$ in equation (9).

LNB shows how a number of market competition can be obtained as special cases of equations (11) and (12), by constraining elements of *R* and E_{Q_T} to be zero. These are summarized in table 1. Entries of each cell in the table include three types of equation forms, depending on the shape of the functional form, i.e. in terms of expenditures, share, or relative form, and major studies belonging to specific functional form categorized by authors. The framework shown in the table clearly indicates the comprehensiveness of this theoretical model.

		Stable industry demand: $E_{Q_T} = 0$	Expansible industry demand: $E_{Q_T} \neq 0$
Oligopoly	No competitive reaction: $R = 0$	$E_{q,u} = E_{m_i,u}$ $= -E_{m_i,U} = E_{m_i,u^*}$ (i) $= D_{U^0} \cdot E_{m_i,u^0}$ (ii)	$E_{q,u} = E_{Q_T,u} + E_{m_i,u}$ $= E_{Q_T,u} + E_{m_i,u^*}$ (i) Bass (1969) $= E_{Q_T,u} + D_{u^0} \cdot E_{m_i,u^0}$ (ii) Schultz (1971)
	Simple competitive reaction: $R = R_d$ (only direct effects)	$E_{q,u} = (\mathrm{I} \vdots R_d) \cdot E_{m_i}$ $= (\mathrm{I} - R_d) \cdot E_{m_i,u^*}$ (i)	$E_{q,u} = (\mathrm{I} \vdots R_d) \cdot (E_{Q_t} + E_{m_i})$ $= (\mathrm{I} \vdots R_d) \cdot E_{Q_T} + (\mathrm{I} - R_d) E_{m_i,u^*}$ (i)
	Multiple competitive reaction: $R = R$	$E_{q,u} = (\mathrm{I} \vdots R) \cdot E_{m_i}$ $= (\mathrm{I} - R) \cdot E_{m_i,u^*}$ (i) LNB (1975) Wildt (1974)	$E_{q,u} = (\mathrm{I} \vdots R) \cdot (E_{Q_t} + E_{m_i})$ $= (\mathrm{I} \vdots R) \cdot E_{Q_T} + (\mathrm{I} - R) E_{m_i,u^*}$ (i) Bultez (1971)
Monopoly: $q = Q, \exists U, R = 0$		$E_{q,u} = E_{Q_T,u}$	

Table 1 - Decomposition of total sales elasticities: $E_{q,u}$

Notes: D_{U^0} - is a diagonal matrix of elements of vector U^0, R_d - has the same diagonal elements as R, but has zero-off diagonal entries. The first condition (i), has been derived from a multiple market share function of the following type, in a relative form $m = \varsigma \left(\frac{p}{P}\right)^{\eta_{m_i,p^*}} \cdot \left(\frac{a}{A}\right)^{\eta_{m_i,a^*}} \cdot \left(\frac{x}{X}\right)^{\eta_{m_i,x^*}}$, where, m = firm market share, p, P = firm price and average price of competitors, a, A = firm advertising expenditures and the ones of competitors, x, X = product quality index and average product quality of competitors, and $\eta_{m_i,x_i} = \frac{\partial m_i}{\partial x_i} \cdot \frac{x_i}{m_i}$. The second condition (ii), has been derived from a market-share function with the decision variables in share-form $m = \varsigma \left(\frac{p}{p+P}\right)^{\eta_{m_i,p^0}} \cdot \left(\frac{a}{a+A}\right)^{\eta_{m_i,a^0}} \cdot \left(\frac{x}{x+X}\right)^{\eta_{m_i,x^0}}$.

Empirical Study in the LNB Framework

Wildt (1974) has done an extensive empirical study of competitive market behavior. He investigated the market for a special product sold predominantly in retail food outlets. The product is purchased by the consumer on an irregular and infrequent basis. Wildt (1974) focused on the competitive behavior of the three major firms in the industry. He assumed that advertising was also endogenous. His structural model was block recursive so that it could be decomposed into two subsystems – the market share equations and the managerial decision variable equations.

The importance of his work is in demonstrating that market share relationships should be estimated simultaneously even when these relationships are seemingly unrelated (the system of market-share equations is contemporaneously correlated). The market share subsystem was estimated by the seemingly unrelated regression (SUR) technique and the managerial decision variable subsystem by the two-stage least squares (2SLS).

Wildt (1974) investigated the existence of primary demand effects and found no expansible industry demand ($E_{Q_T} = 0$). In the LNB framework presented in Table1, Wildt's study belongs to the model of the form $E_{q,u} = (\mathrm{I} \vdots R) \cdot E_{m_i}$, and a multiplicative market share function of the following form, $m_i = \varsigma \begin{pmatrix} advertising \\ expenditures \end{pmatrix}^{\alpha} \cdot (promotion)^{\beta} \cdot \begin{pmatrix} share \\ new\ variety \end{pmatrix}^{\gamma} \cdot \begin{pmatrix} relative \\ price \end{pmatrix}^{\delta}$. Note that this equation includes three different kinds of variables, that is, actual expenditures (u), proportion (u^0), and share term (u^*). We can't interpret his parameter values in the same way as we did in the LNB framework.

In the LNB model, E_{m_i} and R refer to the case of a firm and all competitors, or the case of us versus them; Wildt (1974) presents relationships for each of the three firms in his structural model. This is one of the restrictions with regard to the LNB model. The model treats a firm's competition as a whole, so the market is defined as the subject firm plus all other firms. If the total number of competitors is relatively small, more information and insight into market structures could be gained from considering each competitor separately, provided that the necessary data are available.

Another restriction of the LNB model is that the model doesn't allow for cases of joint marketing decision making, i.e. the possibility that levels of one marketing instrument affect or are affected by levels of other marketing instruments within the (same) firm. The Marketing literature cites many instances of such "in-firm effects" (following our typology of reactions effects we call them "intra-indirect effects), such as the negative relationship between advertising and personal selling or the positive relationship between price and personal selling. As a result, numerous researchers have faced problems in estimating sales responses coefficients because of multicollinearity among the Marketing mix variables.

Before we pass to the analysis of the Hanssens' (1980) extension, a last word about reaction functions and how we should estimate them.

Friedman (1977) defined a reaction function as "a function which determines for a firm in a given time period (t) its action as a function of the actions of (all) other firms during the preceding time period (t-1)". The functional form of these reaction functions has been traditionally restricted to the linear and the multiplicative (double logarithmic) one ($P_t = \xi \cdot p_t^{\rho_{P,p}} \cdot a_t^{\rho_{P,a}} \cdot x_t^{\rho_{P,x}}$ and similarly for the other marketing decision variables). So, when estimated in a simultaneous equation system framework they gave us the estimate elements of the matrix R.

Some times, a firm might react differently to positive or negative changes in a competitor's marketing instrument; i.e. competitive effects can be differentially and asymmetrically distributed. The functional forms that have been used up to now don't allow for these asymmetries.

The Hanssens' (1980) Extension

Hanssens (1980) proposes that models of markets should combine sales response, feedback, and competitive reaction effects. Specifically, a model should make the distinction between primary demand (PD) or industry sales (Q_T) effects and secondary or market share (m_i) effects and between sales response and feedback effects of the marketing mix variables. In addition, competitive activity may change the sales response effects drastically; for example, even though sales response to advertising may be positive, the real effect could be zero because of competitive advertising reactions. A model should be able to detect such situations.

Hanssens (1980) extended the LNB model to incorporate intra-firm effects by the inclusion of intra-firm reaction elasticities in the matrix R. He also extended the LNB analysis to include individual competitors' reaction elasticities.

In what follows, we are going to present the extended R matrix, for the case of three competitors each one manipulating a three-dimensional marketing mix vector (advertising-A, distribution-D, price-P).

Some notation is introduced first.

The matrix of reaction elasticities, R is:

$$R = \left(e_{X_{ij}, X_{k,l}} \right) \tag{13}$$

where $i,k = 1,\cdots,M$ (mix variables), $j,l = 1,\cdots J$ (competitors), X_{ij} – level of the marketing mix variable i of competitor j, e_{XY} – the elasticity of Y with respect to X, i.e. $\frac{dY}{dX}\cdot\frac{X}{Y}$ and $e_{X_{ij},X_{kl}} = 1$ for all $i = k,\ j = l$. The matrix R is of dimension *(JMxJM)*.

We present in Table 2 the extended R matrix for the case in analysis and a typology of reaction effects is also presented.

$$\left(\begin{array}{ccc|ccc|ccc}
1 & e_{A_1A_2} & e_{A_1A_3} & e_{A_1D_1} & e_{A_1D_2} & e_{A_1D_3} & e_{A_1P_1} & e_{A_1P_2} & e_{A_1P_3} \\
e_{A_2A_1} & 1 & e_{A_2A_3} & e_{A_2D_1} & e_{A_2D_2} & e_{A_2D_3} & e_{A_2P_1} & e_{A_2P_2} & e_{A_2P_3} \\
e_{A_3A_1} & e_{A_{13}A_2} & 1 & e_{A_3D_1} & e_{A_3D_2} & e_{A_3D_3} & e_{A_3P_1} & e_{A_3P_2} & e_{A_3P_3} \\
- & - & - & - & - & - & - & - & - \\
e_{D_1A_1} & e_{D_1A_2} & e_{D_1A_3} & 1 & e_{D_1D_2} & e_{D_1D_3} & e_{D_1P_1} & e_{D_1P_2} & e_{D_1P_3} \\
e_{D_2A_1} & e_{D_2A_2} & e_{D_2A_3} & e_{D_2D_1} & 1 & e_{D_2D_3} & e_{D_2P_1} & e_{D_2P_2} & e_{D_2P_3} \\
e_{D_3A_1} & e_{D_3A_2} & e_{D_3A_3} & e_{D_3D_1} & e_{D_3D_2} & 1 & e_{D_3P_1} & e_{D_3P_2} & e_{D_3P_3} \\
- & - & - & - & - & - & - & - & - \\
e_{P_1A_1} & e_{P_1A_2} & e_{P_1A_2} & e_{P_1D_1} & e_{P_1D_2} & e_{P_1D_3} & 1 & e_{P_1P_2} & e_{P_1P_3} \\
e_{P_2A_1} & e_{P_2A_2} & e_{P_2A_3} & e_{P_2D_1} & e_{P_2D_2} & e_{P_2D_3} & e_{P_2P_1} & 1 & e_{P_2P_3} \\
e_{P_3A_1} & e_{P_3A_2} & e_{P_3A_3} & e_{P_3D_1} & e_{P_3D_2} & e_{P_3D_3} & e_{P_3P_1} & e_{P_3P_2} & 1
\end{array}\right)$$

Table 2 – Extended reaction matrix: R

The nine partitions are interpreted as follows. The main diagonal blocks are simple competitive effects, which are by definition inter-firm effects (inter-direct effects). The off-diagonal blocks are the multiple competitive effects. Within these blocks, the elasticities on the main diagonals are intra-firm reactions (intra-indirect effects); that off-diagonal are inter-firm effects (inter-indirect effects).

Classification of reaction effects:

$$\text{Reaction effects - }\begin{cases} \text{Direct effects } (i = k): e_{A_1,A_2},\cdots e_{P_3,P_2}\ :\ e_{X_{ij},X_{il}} \\ \text{Indirect effects } (i \neq k)\ \begin{cases} \text{Intra } (j = l): e_{D_1,A_1},\cdots,e_{P_3,D_3}\ :\ e_{X_{ij},X_{kj}} \\ \text{Inter } (j \neq l): e_{A_1D_2},\cdots,e_{P_2D_3}\ :\ e_{X_{ij},X_{kl}} \end{cases} \end{cases}$$

These competitive reaction coefficients are to be interpreted as dynamic; otherwise, one could not necessarily distinguish the direction of the effects.

When we use elasticities as measures of competition-indicators of market structures, we should be aware of its limitations. Firstly, they are static measures as they assume no competitive reaction to a change in a marketing mix variable. Secondly, because they are static measures, they do not account well for structural change in markets. Thirdly, they can be difficult to measure when, for example, price changes are infrequent or are of low magnitude.

In the Hanssens' paper although historical lags and competitive reactions could be included in elasticities calculations, misspecification of his equation (13´) precluded computation.

Lagged influences on brand i's market-share can be represented as $e_{m_{it},I^k_{jt^*}}$: this is the influence that brand j´s kth marketing mix instrument in historical period t* has on brand i´s market-share in period t. But for a competitive reaction to influence a current elasticity a combination of events must occur. There must be an action involving marketing instrument k´ by some brand i´ in historical period t´ which produces a significant kth reaction by brand j in some historic period t*, and there must be a non-zero elasticity for the effect of brand j´s kth instrument in period t* on brand i´s market-share in period t. The market-share cross-elasticitity is represented as:

$$e_{m_{it},I_j^k} = \sum_{t^*=t-h}^{t} e_{m_{it},I_{jt^*}^k} + \sum_{t^*=t-h}^{t}\sum_{t'=t^*-h}^{t^*}\sum_{k'=1}^{k}\sum_{i'=1}^{M} e_{I_{i't'}^{k'},RI_{jt^*}^k}\cdot e_{m_{it},I_{jt^*}^k}$$

, where h is the maximum relevant historical lag and the reaction elasticities by $e_{I_{i't'}^{k'},RI_{jt^*}^k}$, where the subscripts before R indicate the antecedents producing the reaction, while the subscripts after R indicate where they occur. Note that if either $e_{I_{i't'}^{k'},RI_{jt^*}^k}$ or $e_{m_{it},I_{jt^*}^k}$ is zero, the entire term makes no contribution to e_{m_{it},I_j^k}. This reaction chain can be represented as:

------- | t´-------------------------- | t*-------------------------- | t--------
lag of h periods lag of h periods

$$I_{i't'}^{k'} \xrightarrow{Action(\mathrm{R})} I_{jt^*}^{k} \xrightarrow{\text{Reaction}} m_{it}$$

$$\uparrow \ \text{Instantaneous}$$

$$|$$

$$I_{i't'}^{k'} \quad (t' \equiv t^*)$$

In spite of the simplicity of this mechanism, estimation problems are difficult to solve, mainly, how to specify *h* and how do we know the actions, $I_{i't'}^{k'}$?
In this framework, the LNB equation is extended to as follows:

$$\eta_s = R\left(\eta_{PD} + \sum_{j=1}^{J} T^{(j)}\cdot \eta_{m_j}\right) \qquad (14)$$

where $T^{(j)}$ is a dummy-variable matrix of dimension (JM*JM) for competitor j , defined as $T^{(j)} = \{T_{kn}^{(j)}\}$, where $T_{kn}^{(j)} = \begin{cases} 1, & k = j, j+J, \cdots, j+(M-1)J \\ 0, & \text{elsewhere}, \qquad \forall n \end{cases}$, η_s - is a (JM*1) vector of sales elasticities of each firm's marketing variables, η_{PD} - is a (JM*1) vector of primary demand elasticities of the mix variables, and η_{m_j} - is a (JM*1) vector of competitors j´s market share elasticities of i´s marketing variables and all competitors marketing expenditures (that is, the cross elasticities).

In the preceding example with three competitors and three marketing instruments, the matrices $T_{(9\cdot 9)}^{(j)}$ would be:

$$T^{(1)} = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{pmatrix}, \quad T^{(2)} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \end{pmatrix}, \quad T^{(3)} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$

These dummy variables are needed to post-multiply the vector of market share elasticities with the appropriate elements of the reaction matrix R.

Several special cases can be derived from equation (14) by imposing restrictions on the elements of R and (or) by constraining the vector η_{PD} to be zero. For example, no primary demand effects, that is, stable industry: $\eta_{PD} = 0$, no competitive reactions: $R = \mathrm{I}$, an identity matrix of dimension JM, no intra-firm effects: $e_{X_{ij}X_{kl}} = 0\ ,\ \forall j = l$, and only simple competitive reactions in the market: $e_{X_{ij}X_{kl}} = 0\ ,\ \forall i = k$.

The theoretical model (14) is an abstract representation of a market mechanism. It describes a relationship among market parameters, which must be estimated. Hanssens (1980) proposes an integrated approach (a time series-econometric analysis) to estimate the components of equation (14). The author proposes that principles of multiple time series analysis in a three-stage model building methodology be used on the extended model as follows: Firstly, develop univariate ARIMA models for primary demand, market shares, and the various marketing mix variables and save the white–noise ARIMA residuals. Secondly, tests the null hypothesis of independent series by cross-correlating the ARIMA residuals with each other for the cases of interest, i.e., primary demand effects, market share and cross-share effects, intra-firm and inter-firm reactions. Use Haugh’s chi-square test and inspection of individual cross-correlations to reach verdicts. In his framework, a time series causality test is used for the specification of zero and nonzero elements in the extended LNB model. The shape of the cross-correlation function can also be used to determine the carryover-effects of the marketing mix variables, in general, to help specify the dynamic-causal structure of a system. Thirdly, specify the zero and non-zero elements in model (14). The form of the resulting model will determine the method of parameter estimation to be used, for example OLS on single response equations or 2SLS on a group of equations.

Once the non-zero elements identified, different sources of information (prior knowledge of the market, for example, managers can be a valuable source of information in specifying intra-firm effects as well as Economic and Marketing theory can be used to specify the functional forms for the primary demand equation, market share and reaction systems.

Hanssens (1980) applied his framework to the analysis of a city pair in the domestic (USA) air travel market.

The field of optimal marketing decision models has evolved significantly, driven by advances in artificial intelligence (AI), machine learning (ML), and data-driven analytics. Recent studies emphasize the need for integrating real-time consumer insights, predictive analytics, and dynamic pricing strategies to optimize marketing decisions (Yao et al., 2025).

AI-Driven Marketing Decision Models

A major trend in recent research is the incorporation of AI and machine learning in decision-making frameworks. AI-based models can analyze vast consumer datasets to predict purchasing behaviors, allowing companies to adjust pricing, promotions, and inventory dynamically. Similarly, sentiment analysis combined with ensemble learning techniques is being used to enhance stock market predictions and consumer trend analysis, thereby influencing marketing strategies (Chaudhari and Mahajan, 2025).

Game Theory and Competitive Marketing Strategies

Recent studies have also explored game-theoretic approaches in marketing decision-making. Mixed duopoly models have been developed to optimize decision-making in competitive environments, ensuring that businesses can maximize profits while maintaining market share (Yao et al., 2025). Additionally, green supply chain models have integrated subsidy strategies to optimize marketing decisions in eco-conscious markets.

Predictive Analytics and Real-Time Decision-Making

The ability to leverage real-time data has become a critical factor in optimizing marketing decisions. Cloud-based analytics platforms enable marketers to make rapid adjustments to campaigns, pricing, and distribution strategies. Furthermore, hybrid decision models incorporating both human expertise and automated systems have been shown to improve the efficiency of marketing operations (Chen and Tian, 2025).

Future research is expected to focus on the integration of AI-powered decision models with behavioral economics to better understand consumer psychology. Additionally, reinforcement learning techniques will play a growing role in adaptive marketing strategies, allowing businesses to optimize decisions dynamically based on consumer engagement and market shifts.

The Issues of Asymmetric Competitive Marketing Behavior and The Prediction of Competitive Marketing Behavior

Asymmetric competitive marketing behavior occurs when firms in a market do not respond symmetrically to competitive actions due to differences in market power, resources, or strategic positioning.

The rest of the study will be developed to the discussion of some critical issues not presented in the Hanssens' framework. The issues are the asymmetric competitive marketing behavior and the prediction of competitive marketing decision variables.

The competition is called asymmetric when the effects of a brand´s marketing actions are distributed among its competitors out of proportion to their market shares, i.e. if brands A and B are perceived by consumers as being close substitutes of one another, a price cut initiated by A may will affect the share of B more negatively than the shares of other competitors. This is an example of an asymmetric response to prices. These asymmetries may exist for all elements of the marketing mix. Asymmetries in competition arise from two main sources: Firstly, some brands may have unique features of their strategy which either shields them from competitors' marketing actions, or which make them particularly vulnerable to such actions. Secondly, asymmetries can arise from period-to-period variation in marketing mix elements such as relative advertising expenditures or prices.

In the Hanssens' work, the multiplicative log-linear form of the market-share equations and the reaction functions doesn't take in account this effect.

Carpenter, Cooper, Hanssens and Midgley (1988) present and illustrate methods for modeling brand competition and brand strategies in markets where competitive effects can be differentially and asymmetrically distributed. They begin with the extended attraction model (EAM) or cross-effects model, which includes market asymmetries by adding special attraction components. The general form of the attraction model for brand i , with advertising and price as marketing mix elements is,

$$m_{i,t} = \frac{e^{(\alpha_{i,0}+u_{i,t})} \cdot \prod_{j=1}^{M} \alpha_{j,t}^{\beta_{1,ij}} \cdot p_{j,t}^{\beta_{2,ij}}}{\sum_{k=1}^{M} \prod_{j=1}^{M} \alpha_{j,t}^{\beta_{1,kj}} \cdot p_{j,t}^{\beta_{2,kj}} \cdot e^{u_{k,t}}} \qquad (15)$$

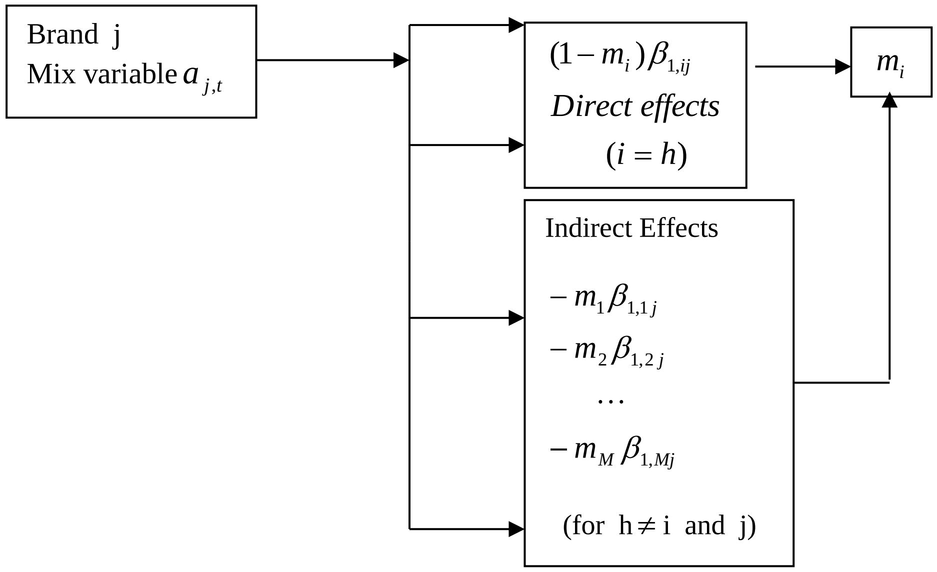
where $j,k = 1,\cdots,M$ are brands or competitors.

The most important property of the model is the existence of cross-effects parameters: $\beta_{1,ij}, \beta_{2,ij}$. $\beta_{1,ij}$ is the parameter of the cross-competitive effect of brand or competitor j's advertising on brand's i market-share. The attraction for brand *i* is now a function not only of the firm's own actions (variables $a_{i,t}, p_{i,t}$) but also of all other brand's actions (variables $a_{j,t}, p_{j,t},\ j = 1,\cdots,M$). The $\beta_{1,ij}, \beta_{2,ij}$ for which i is different from j are the cross-competitive effects parameters which partly determines cross-elasticities. $\beta_{1,ij}, \beta_{2,ij}$ for which j equals i ($\beta_{1,ii}$) are direct-effects parameters.

The direct and cross-elasticities for this model are expressed (Cooper and Nakanishi, 1988, page 62) by the formula,

$$e_{m_i, I_j^1} = \beta_{1,ij} - \sum_{h=1}^{M} m_h \cdot \beta_{1,hj} \ ,\ \text{h} = 1,\ldots,\text{M (brands)}$$

.If i equals j , the above formula give direct elasticities for brand i , otherwise they give cross-elasticities. e_{m_i, I_j^1} is the elasticity of market-share for brand *i* with respect to changes on the advertising for brand j and it is given by $\beta_{1,ij}$ minus the weighted average of $\beta_{1,hj}$ over h , where the weights are the market-share of respective brands (m_h). We can decompose this elasticity as:



We assume that the brand's j mix variable is advertising.

Such a model clearly puts too many demands on the data, and so the critical question is how to distinguish between fundamental or systematic asymmetries and those that are small enough so that they can safely be set to zero.

Market asymmetry manifests when firms respond differently to similar market conditions, often due to variations in brand reputation, pricing power, and consumer perception. For example, firms with stronger brand equity can sustain price increases without significant demand loss, while competitors with weaker brands face a steeper decline in market share when implementing similar strategies. This asymmetry creates market inefficiencies and competitive imbalances, making it challenging for smaller firms to compete effectively.

Understanding asymmetric competition allows firms to tailor their marketing strategies based on competitor weaknesses and consumer perceptions. Hofmann (2024) examines the role of bargaining power in asymmetric competition, showing that firms with a stronger negotiation position can extract greater value from strategic alliances and partnerships. His findings underscore the importance of strategic positioning in mitigating the risks of market asymmetry.

Future research should focus on integrating AI-driven predictive models with behavioral economics to further refine competitive marketing decision-making. As markets become increasingly digitalized, firms must adopt more advanced analytical techniques to anticipate competitor moves and maintain a competitive edge.

Prediction of Competitive Marketing Behavior

We have assumed up to now that the future behavior of competitors (what are the expected levels of the marketing mix variables of competitors?) is known, that is, they react as they have done in the past. In the Marketing Literature, three approaches have been suggested to deal with this question: Gatignon, Anderson and Helsen (GAH) (1989), Alsem, Leeflang and Reuyl (ALR) (1989), and Chen, Smith and Grimm (CSG) (1992)

In the first approach, competitive reactions can be predicted by observing, for each competitor the elasticity of each marketing mix variable, i.e. e_{m_i,I_i^l}, where I_i^l is the lth marketing mix variable of competitor i . They assume that each competitor will react with the instrument for which the e_{m_i,I_i^l}, $l=1,\cdots,k$ is the highest – more elastic (the authors use as a decision criterion, the e_{m_i,I_i^l} and not the cross-elasticities of the established firms). These elasticities are obtained by estimating by econometric and (or) time series methods, demand or market-share response functions and reaction functions. In a first step, they estimate for each brand, a multiplicative log-linear market-share model ($\hat{e}_{m_i,I_i^l}$). A SUR (more accurate estimates, with reduced estimators' variance, are obtained when compared with OLS ones) method is applied to the entire system of market-share equations in the case of contemporaneous correlations presence. This first step permits us to choose the decision variables that should be modeled in the second step. The decision equation must incorporate inter-firm coordination of mix variables and reactions to competitors, both with lags in reactions and anticipation of competitors' actions. The reaction elasticities obtained from the system of decision equations (estimated by time series methods in the case of sufficient data or by SUR methods otherwise) give us the correct information about the asymmetry of competitive behavior.

In the second approach, ALR (1989) investigate the sensibility of market-share predictions to different assumptions about future competitive behavior: Firstly, market-share predictions are not sensitive to the assumptions that are made with respect to future competitive behavior. Secondly, using predicted values of competitive behavior may provide better market-share predictions than observed values of competitive behavior.

They tried to answer the question – what is the best method for forecasting how competitors set the levels of their marketing mix variables? – by formulating two kinds of models: (i)- a naïve model: $I_{i,t}^{l} = f\left(I_{i,t-1}^{l}\right),\ l = 1, \cdots, k \ \text{(instruments)}$, and (ii)- a sophisticated (econometric) model. In this case $I_{i,t}^{l}$ is determined by four groups of variables: its own marketing instruments, environmental variables represented by dummies, lagged dependent variables, and lagged market-shares

In the third approach (CSG), the authors used a formal empirical framework to identify the characteristics of actions that lead to competitive reactions. The hypothesized relationships were tested with a sample of competitive moves among US airlines. They found that the number of competitive reactions is positively related to the competitive impact and the attack intensity. Actions with great implementation requirements and strategic (versus tactical) actions provoke fewer counteractions. Strategic actions and actions which require a substantial amount of time generate slower reactions.

In their approach, one of the predictors of competitive reactions is the attack intensity, that is, "the extent to which an action affects a given competitor's key markets". They employ variables that should logically be related, e.g., the number of reactions is a positive function of the number of competitors potentially affected by an action.

Machine learning models have also been applied to predict competitive marketing actions. A study by Guerra et al. (2024) introduces a quantile-based dynamic modeling approach that captures asymmetric behaviors in competitive environments. By analyzing historical market trends, their model improves the prediction of pricing strategies, promotional intensity, and competitive reactions, offering firms a more data-driven approach to market decision-making.

Additionally, Briola (2024) explores deep learning models for stock market forecasting, demonstrating that firms' competitive behaviors in financial markets exhibit similar asymmetric patterns seen in traditional marketing environments. His research suggests that integrating deep learning with economic theory can improve the accuracy of competitive behavior predictions.

Conclusions

It has been assumed in this review that the competitive conditions in a market may be described by a set of model parameters, especially the elasticities of market shares with respect to marketing variables. However, we recognize that designing a marketing program based on the knowledge of elasticities is not an automatic process. With only a limited number of brands and marketing variables one may have to deal with a surprisingly complex pattern of competitive interrelationships, indicated by the large number of elasticities and cross-elasticities. The manager needs to interpret such a pattern and to select one set of levels for the marketing variables which presumably maximizes the firm's (long-term) profits. But there are no easy rules for converting a given pattern of competition into a manageable marketing program.

Some might think of designing marketing programs as large-scale mathematical-programming problems, but such a conception is unrealistic for several reasons. For one thing, the future environment for a firm's marketing program is full of uncertainties, which affect its performance. Economic conditions change unexpectedly; variations in consumer tastes are sometimes illogical; weather and climate substantially impact demand, etc. Statistical methods may be employed to cope with future uncertainties, but its applications to modeling competitive marketing behavior is complicated by the fact that those factors that cause uncertainties must be explicitly bought into the model and the strength of their influence must be calibrated beforehand. Many important factors cannot be treated in this manner. How, for example, does one calibrate the impact of one-time events, such as new governmental regulations?

For another thing, even if other uncertain factors can be correctly guessed, the best (optimal) marketing program for a firm is still dependent on the often-unpredictable actions of the competitors. One may guess competitors' marketing actions and plan one's own program accordingly. But will they guess that our actions are about to be modified and adjust their actions again?

Lastly, designing an optimal marketing mix, i.e. the best combination of marketing variables, presumes the existence of a definite objective. In formal theories the objective is assumed to be maximizing either long-run or short-run profits, but in many practical decision situations profit maximization is not always pursued. The real-world managers may have difficulties in conceptualizing long-run profits, yet they are too astute to try to maximize short-run profits. In the context of modeling market shares, it is often a planned level of market share that becomes the main objective and is pursued vigorously. There is no sophisticated theory (Statistical or Econometric) which enables one to find an optimal marketing mix when one is not sure of the objective to achieve.

This review on Modeling Competitive Marketing Behavior reinforces the necessity of integrating contemporary econometric and AI-driven models to enhance decision-making in dynamic markets. Traditional models, such as those proposed by Lambin, Naert, and Bultez (1975), remain influential in understanding firm interactions. However, recent advancements, particularly in machine learning and AI-powered forecasting, have refined competitive strategy modeling (Nweke, 2025).

A major insight from recent research is that firms must account for asymmetric brand competition, multi-channel market interactions, and dynamic cross-effects (Chukwurah et al., 2025). Businesses are increasingly leveraging AI and big data analytics to anticipate competitors' pricing and advertising responses, reducing uncertainty in strategic marketing (Ling & Weiling, 2025). Moreover, predictive modeling and real-time consumer behavior tracking have become central to competitive marketing strategies (Duche-Pérez & Olger, 2025).

Emerging research highlights the importance of hybrid modeling approaches that integrate econometrics with AI-driven decision-making systems. The use of structural equation modeling (SEM) and deep learning-based simulations has improved the accuracy of competitive behavior predictions, enabling firms to optimize resource allocation and mitigate market risks. Furthermore, sentiment analysis and reinforcement learning have facilitated better adaptation to shifting consumer preferences, leading to more effective targeted marketing strategies.

Future research should focus on the integration of generative AI in competitive strategy formulation, as well as the development of adaptive models that incorporate real-time market data. The convergence of AI-driven analytics, behavioral economics, and traditional marketing theories is likely to redefine competitive dynamics, ensuring firms remain resilient in evolving markets.

In conclusion, the evolution of competitive marketing behavior modeling underscores the increasing complexity of market interactions. Businesses that successfully integrate AI-driven insights into their strategic frameworks will be better positioned to navigate competitive landscapes and optimize marketing performance in real time.

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