Competitive Reactions to Market Entry: Explaining Interfirm Differences

In a Journal of Marketing Research editorial, Weitz (1985, p. 229) notes:

The effectiveness of marketing programs usually depends on the reaction of both customers and competitors. However, marketing theories and research have emphasized issues related to customer response and have directed less attention to competitive response. This lack of attention to competitive effects is surprising because it is difficult to imagine a marketing decision that is not affected by competitive activity.

Weitz goes on to call for empirical research to identify patterns of competitive response under a variety of conditions.

Our research is a step in that direction. We examine competitive response to an event that can profoundly affect a firm or even an entire industry: the entry of a new competitor (Baumol 1982). How will established firms react to this potentially momentous event? Scherer (1980, p. 244) outlines the possibilities as either accommodation (cutting back to “make room for the newcomer”) or retaliation (fighting back to “make life as difficult as possible for the interloper”) and calls for economists to build “realistic theories” about which reaction to expect. The strategy literature amplifies, pointing out that different competitors not only choose different reactions but differ in how they employ specific “instruments of warfare” (Kotler and Singh 1981). For example, firm A may react by increasing advertising, firm B may cut price, and firm C may alter none of its marketing mix decisions (Hanssens 1980; Lambin, Naert, and Bultez 1975).

In sum, each competitor decides, for each marketing instrument, whether to respond to an entrant by counterattacking (raising expenditures, a positive reaction), retreating (reducing expenditures, a negative reaction), or not responding (a zero reaction). Predicting these reactions is an important component of strategic marketing (Oxenfeldt and Moore 1978; Porter 1979; Rothschild 1979). Predicting competitive reactions in detail is a...
COMPETITIVE REACTIONS TO MARKET ENTRY

complex, subjective endeavor and often is based on dubious personifications of each competitor (Day 1984; Miles 1980). Though broad guidelines have been suggested (in particular, in the industrial organization literature), they often yield conflicting predictions. Further, these guidelines come from normative models whose applicability to actual situations has not been assessed.

The purpose of our study is to develop and test an explanation of when and why some firms (or brand managers in the case of multiproduct firms) in a given market react negatively to a market entry, others react positively, and others do not react at all. We survey the strategic and industrial organization literatures and array their arguments into reasons for expecting negative or positive reactions. We concentrate in particular on the explanation of variations in reaction across competitors and marketing instruments. We then suggest a contingency approach based on the principle that competitors fight only with their "best weapons" and avoid doing battle with their "poor weapons" (Kotler and Singh 1981). We propose that good weapons are marketing mix variables that the firm uses well—those for which the market response is relatively elastic. Conversely, poor weapons are marketing mix variables that induce a small change in the firm's sales or market share performance. Elasticity, which measures the percentage change in the market's response to a brand due to a percentage change in one of the marketing variables of that brand, is thought to be an indicator of the strength of that marketing instrument.

Our fundamental proposition is that each established competitor reacts to an entrant that threatens its position by raising expenditures on variables with relatively high elasticities and by lowering expenditures on variables with relatively low elasticities. Here, we consider market response in terms of shifts in market share. We offer a test of these ideas using an econometric model of competitive rivalry in the market for an over-the-counter gynecological product and we replicate the results in the airline industry.

COMPETITIVE REACTIONS: CONFLICTING THEORIES AND CONTINGENCY PROPOSITIONS

Overview

The theoretical literature bearing on competitive reaction comes largely from industrial organization (IO) and strategy, whereas much of the empirical research comes from marketing. An oft-noted feature of the IO literature is its emphasis on structure (number and size of competitors), from which behavior ("conduct") is inferred (Scherer 1980; Weitz 1985). This literature is covered thoroughly by Scherer (1980). In contrast, the strategy literature is concerned directly with the actions of each competitor (Miles 1980). These literatures are a rich source of rationale for hypotheses.

Perhaps because of the difficulty of obtaining comprehensive data on competitor behavior, empirical research or competitive research is relatively sparse (Scherer 1980; Weitz 1985). Empirical marketing research on competitive rivalry or reactions has concentrated on the difficult issue of how to measure the extent of rivalry. Apart from market share models, the first econometric models explicitly incorporating competition did so by introducing competitive marketing efforts as independent variables (Bass and Parsons 1969; Beckwith 1972; Clarke 1973; Schultz 1971). Then Wildt (1974) explicitly modeled rivalry in a system of equations where the marketing decisions were endogenous. Further developments in the measurement of reactions and the effects of competitive reaction on optimal decisions have been offered by Lambin, Naert, and Bultez (1975), Metwally (1978), and Hanssens (1980). This work has advanced the study of competition to the point that a state of rivalry can be observed and measured (Hanssens 1980), thereby overcoming a very difficult barrier to empirical study of the impact of competitive reactions.

We focus on how established firms in an oligopoly react to the entrance of a new competitor in their market. The purpose of our study is to investigate why there are differences in the direction of response (positive or negative) among firms in a given market. This research question is motivated by the empirical finding that firms do not all react in the same direction. For example, some firms might react to a competitor's increase in advertising expenditures by increasing their own or, conversely, by decreasing them. Further, firms may not react at all, showing zero or insignificant reaction elasticities (Gatignon 1984). Such differences in reaction to the same event—a market entry—are due partially to variations in the perceptions of the relevant organizational members and in the enactment processes by which individual perceptions become corporate viewpoints (Day 1984; Miles 1980; Oxenfeldt and Moore 1978; Rothschild 1979). Differences in reaction also may depend on the agendas and values of influential individuals within the established firms in an industry (Cyert and March 1963; Williamson 1965). Unfortunately, these factors are difficult to study systematically; their effect may be to introduce "noise" into the relationship between competitive actions and reactions. However, another factor—differences in firm abilities—operates in a more systematic way and is more amenable to theory development. Firm abilities are the focus of our study.

Writers in strategy point out that some firms are simply very good at some functions (e.g., advertising) and very poor at others (e.g., distribution). Several scholars, notably Porter (1979) and Day (1984), build their approach on the identification of each competitor's "vulnerabilities" and strengths (competitive advantage). Such knowledge is useful not only in deciding where a firm should attack, but also in predicting where it will be attacked and what weapons each competitor is likely to use. The prevailing (and reasonable) assumption is that firms will use only the weapons they wield well. In the following sections we first discuss reasons to expect neg-
negative or little reaction, then reasons to expect positive reaction.

**Negative Reaction (Withdrawal)**

We suggest that established competitors may respond to entry by cutting back resources devoted to a market for two reasons: inability to formulate an effective response and the possibility that withdrawal is the optimal (profit-maximizing) response.

*Inability to respond effectively.* Committing resources to battle presumes one knows how to fight back. Devising a counterattack is not difficult for some kinds of competitive action, but for others the appropriate response is unclear (Schmalensee 1976). As Scherer (1980, p. 388) puts it, "... any fool can match a price cut, but countering a clever advertising gambit is far from easy." Countering an entrant (likely to be something of an unknown quantity) is also far from easy. Hence, in the face of uncertainty about how to respond, some firms may respond very little, if at all. Firms may even reduce resource commitments, either permanently or while waiting to determine how the market will react to the entrant (Cooper and Schendel 1976; Kotler and Singh 1981).

A firm also may cut back because it is certain that it cannot counter effectively (Day 1984; Oxenfeldt and Moore 1978). As Rothschild (1979, p. 23) states, "If the key skills aren't available, the competition will have less than optimal results."

**Negative reaction as a profit-maximizing response.** One approach to the question of reaction to entry is offered by the DEFENDER model (Hauser and Shugan 1983). This normative analytical model predicts the optimal (profit-maximizing) response to entry given a set of assumptions about the market. Under a range of conditions, some degree of negative reaction proves optimal (profit maximizing) for the three variables considered: advertising (cut expenditures), distribution (cut expenditures), and pricing (raise price). One reason for these results is that, under Hauser and Shugan's assumptions, the entrant usually decreases every other competitor's profit, making the market less worthwhile. Hence, expenditures generate lower returns after entry and established competitors will have an interest in not committing the same level of resources. An inherent assumption, however, is that the market does not expand as the result of the product introduction.

**Positive Reactions (Retaliation)**

Firms may respond to entry by positive reactions (increasing marketing expenditures to combat an entrant) for two reasons: objectives other than profit and underspending.

*Objectives other than profit.* The DEFENDER model's recommendation to cut back in response to market entry follows from two premises: firms behave rationally and they seek to maximize profit. An extensive literature in organization theory establishes the possibility that firms behave irrationally (e.g. Cohen, March, and Olson 1972). It is also possible that, for a given brand or strategic business unit (SBU), the objective is not profit maximization but is instead market dominance, maintenance of a niche, or some other goal not related directly to brand or SBU profit. Such objectives can lead to a "fight back" response (positive reaction) even at the expense of profit.

**Underspending.** Analytical models usually assume that all firms operate at a level of marketing expenditures such that the elasticity of each marketing variable is less than one (decreasing returns to scale). This is also an assumption of the DEFENDER model (Hauser and Shugan 1983). However, if this assumption is violated (increasing returns to scale), negative reactions will not maximize profit because a firm is already underspending. Hence, further cutbacks perpetuate the underspending error. Firms that are underspending may have positive rather than negative reactions because positive reactions may be the profit-maximizing response for them.

A firm might underspend for several reasons, even though doing so is normatively incorrect. First, managers may be ignorant (at least initially) of the elasticity of a marketing mix variable (Chakravarti, Mitchell, and Staelin 1981); they may not be aware they are underspending. Second, to find where they are on the sales response curve, firms would need to experiment, which they typically hesitate to do (Ackoff and Emshoff 1975; Little 1966; Pekelman and Tse 1980). Third, firms might not be able to increase their effort substantially to reach the zone of optimal returns (e.g., because of lack of budget for advertising or lack of access to channels of distribution). Fourth, as Hauser and Shugan (1983) note, some industries are "sleepy" (not very competitive).

The entrant may "wake up" the industry, galvanizing competitors to use marketing mix instruments as they should be used. In essence, entry heightens competition, which forces a firm to reexamine its practices and correct errors, such as spending too little on a marketing mix variable. This "error correction" is observed as a positive reaction to market entry.

**A Contingency Approach to Competitive Reaction**

If positive, zero, and negative reactions can vary by both competitor and marketing instrument, how can a given competitor's reaction be predicted? Though we cannot hope to provide a complete answer, we suggest that the direction of competitive reaction is contingent upon the elasticity of a firm's marketing mix variables. We propose that firms react positively (increase expenditures) with their best weapons—the marketing instruments that have relatively high elasticity. Conversely, firms react negatively (decrease expenditures) with relatively inelastic marketing instruments. If firms react negatively when elasticity is low and positively when elasticity is high, it follows that there is a "turning point"—the level of elasticity where no reaction would occur. In practice, given the uncertainty of the assessment of elasticity, there is a zone of elasticity within...
COMPETITIVE REACTIONS TO MARKET ENTRY

which no reaction would be expected.
The preceding discussion leads to the following propositions.

P₁: A firm with low marketing effort elasticity for a given variable reacts to an entry by decreasing its effort for that variable.

P₂: As the elasticity of a marketing variable increases, the firm reacts to an entry by decreasing its effort by lesser increments. At some point, the firm’s reaction turns positive, that is, the firm reacts to entry by increasing its effort for that variable.

P₃: A firm with high marketing effort elasticity for a given variable reacts to an entry by increasing its effort for that variable.

P₁ proposes a zone of negative reaction, P₂ a zone of no reaction, and P₃ a zone of positive reaction.

AN EMPIRICAL TEST OF THE CONTINGENCY APPROACH TO COMPETITIVE REACTIONS

Our propositions are tested in two industries. Though this test may not generalize across all industries, its replication offers evidence about the existence of the hypothesized phenomenon that is not idiosyncratic to a particular industry. We first describe the data for each market/industry studied. Then, because the procedures followed in the two cases are identical, we discuss each step of the process and the results of each step for both datasets in parallel.

Data

Over-the-counter gynecological product. Our first dataset is from the market for a women’s health care product that can be purchased over the counter. The product, which can be used once only, was formerly available only through a visit to a doctor’s office. Once approved by the Food and Drug Administration as an over-the-counter product, the first brand was launched in the late 1970s and was an immediate success. By 1982 the industry was large and competitive. For proprietary reasons the nature of the product cannot be described in greater detail. We refer to the product as “OTC-gyn” (over-the-counter gynecological product).

Quarterly data are available from January 1982 to June 1986, a period of intense competition centering around a few national brands, including two major entries. In our analysis, we consider four established brands for which data are available through the period and two entrants. The four established brands (brands A, B, C, and D) were the “major players” in this market during this period, with a combined market share of more than 90% before the entries of two new brands, which we study. Three of the four brands use advertising as their principal marketing mix instrument. Because the market changes quickly, test marketing and rollouts are rare. Brands typically go from concept test to national launch, which allows pinpointing of entry periods.

We use Nielsen data for the dependent variable, market share in units. The predictor variables are represented by proprietary advertising data on all major competitors. Prices were relatively stable during the period investigated and, with the exception of brand C, there were few price differences among the brands available during that period.¹ Brand C is a low priced brand that did virtually no advertising. Given that media expenditures are on a quarterly basis, we transformed the market share data from their original bimonthly basis to a quarterly basis by a straightforward linear smoothing technique.²

The OTC-gyn industry consists of three types of products, which have different benefits and drawbacks and coexist in the market. The “first generation” is effective but is relatively easy to misuse unintentionally. One brand entry (brand E), introduced in quarter 3 of 1985, is of this type. “Second-generation” products, introduced in the early 1980s, are less sensitive to mishandling. One established second-generation brand, A, was extended with the addition of a variant we label “brand A-plus,” introduced in the first quarter of 1984. “Third-generation” products are exceptionally easy to use and have a very different appearance. Qualitative research indicates the third-generation products appeal to many consumers who believe they carry a more medically “correct” connotation. Brand F, whose entry is included in our data, is the first brand of this form and was launched in quarter 4 of 1984.

Airline market. In this industry, competitors are large, the ratio of fixed to variable costs is high (which, according to Porter 1979, would make positive reactions more likely), and the product line is flexible (the product is a flight and the flight schedule is not difficult to vary). The relative flexibility of the number of flights should increase the likelihood of observing any change in this decision variable over time. Further, the environment became particularly hostile and uncertain after deregulation (Robertson, Ward, and Caldwell 1982). Indeed, the marketing literature has shown the occurrence of competitive reactions in this industry, some firms reacting positively and others negatively (Gatignon 1984; Hanssens 1980; Wildt 1974). Empirically, the industry is relatively tractable because the impact of a new entry in the market is fast, as are competitors’ reactions, so

¹ Though price data were not available to verify this information, which was provided by the manager of one of the brands, it is congruent with the nature of the product, a high-involvement, occasional purchase that is not expensive in absolute terms. In addition, the goodness of fit of the empirical models reported hereafter indicates that the variables included in the model explain most of the variances in market share, suggesting that relatively little would be left to explain by additional variables such as price.

² Though higher degrees of freedom would be available by disaggregating the advertising data, error in measurement of the independent variables introduces a bias in the estimated model parameters, which is not the case for measurement error in the dependent variable (only inefficiency results because of heteroelasticity). Therefore, it is preferable to sacrifice degrees of freedom for unbiasedness of coefficient estimates (Judge et al. 1985).
effects should not be confused by lags and inertia. As there are few significant marketing mix variables, the "noise" created by the effects of multiple changes in the marketplace is avoided (Gatignon 1984; Schultz 1971; Schultz and Hanssens 1977).

The market (Los Angeles–Phoenix travel) was selected because it met the criterion that an entry occurred after deregulation, when the market became much more competitive. The time series corresponds to the 24 months (January 1979 to December 1980) following deregulation. This series is long enough to estimate elasticities with reasonable precision without jeopardizing the stability of other environmental conditions.

This period corresponds to the time of observation when Gatignon (1984) demonstrated the importance of competition in the last phase of airline industry deregulation (Graham, Kaplan, and Sibley 1981). The time series is observed before deregulation destabilized this industry. There are three competitors, all with similar market shares (.342, .393, and .265), and none in a dominant position. Competitor 3 is a national carrier, for which this route's revenues constitute a small portion of total sales, and competitors 1 and 2 are large regional airlines. The new entrant (competitor 4), which is also a large regional carrier, started operating on this route in April 1980. During this time period, the volume of passengers flying the route varied greatly but without any major trend. The entry did not significantly affect primary demand.

The dependent variable used in the study is the share of the number of passengers on direct flights on the Los Angeles–Phoenix route. Past research (Gatignon 1984; Hanssens 1980; Schultz 1971; Schultz and Hanssens 1977) has shown that the number of flights is the most significant predictor of the number of passengers carried by an airline. Advertising expenditures in the city pair also contribute, though to a lesser extent, to predicting either the number of passengers or market share of an airline on a given route. In addition, after deregulation, price became a significant explanatory variable as well. Gatignon (1984) defined price as the “average lowest fare (one-way) weighted by the duration of that lower fare during the month,” where the fares considered were only those without restrictions on types of individuals or on capacity. Following this prior literature, we used as independent variables the share of the city-pair advertising expenditures (obtained from the Media Records Green Book and from Broadcast Advertisers Reports, Inc.), the relative number of flights, and the relative price. These data were obtained from records of the Federal Aviation Bureau (FAB). Though no significant pattern or trend could be observed in the number of flights or advertising series, a clear trend of increasing prices occurred in this market during the period. However, the relative price measure shows variability over the period.

**Model Specification**

The same procedure was used for both the OTC-gyn product data and the airline route data, which were modeled separately. Our data analysis proceeded in three stages. In stage 1, we estimated, for each brand, a model of market share as a function of the marketing mix variables (e.g., advertising share, relative price or number of flights, lagged market share, and dummy variables representing the two entrants and one product line extension for OTC-gyn brands and one entrant for the airline route). This stage yielded estimates of marketing mix elasticities, as well as the impact of each entry. In stage 2, we modeled the marketing mix decisions (advertising for the OTC-gyn market and number of flights for the airline industry) of each brand as a function of competitive activity. In stage 3, we modified the marketing variable decision functions, introducing a constraint on the coefficients that reflects the impact of an entrant on decisions about advertising spending or number of flights. This constraint takes the form of a process function, wherein the degree of reaction is expressed as a function of the brand’s advertising elasticity (OTC-gyn) or of the number-of-flights elasticity (airlines). The coefficients of the process function form the test of our hypotheses.

**Market share equations.** The market share equations were specified, as is commonly done in econometric models in marketing (Beckwith 1972; Lambin 1976; Parsons and Schultz 1976), as a function of lagged market share and share of marketing mix expenditures. For the airline model, quarterly dummy variables were introduced to capture the seasonality of the market. The lagged dependent variable represents the dynamics of market share. It is a commonly used formulation that tends to contribute to the robustness of the market share model (Naert and Leeflang 1978). The functional form is linear in the logarithms, so the coefficients are interpretable as elasticities. Competitive effects were captured by using each brand’s share of industry advertising (OTC-gyn) or number of flights and relative price (airline). In addition, we introduced dummy variables to represent the impact of each entry.

In the OTC-gyn market, there were two new entries, brand F and brand E, as well as the product line extension of brand A (A-plus). Each brand equation is therefore of the form:

\[
m_{i}(t) = e^{\beta_{0}}m_{i}(t-1)^{h_{1}+\lambda_{i}(t)}h_{2} \prod_{k=1}^{3} e^{h_{3}+\lambda_{i}(t)}\rho_{j}(t)
\]

The new entry may influence consumers’ responses to the marketing mix variables, thereby changing elasticities and cross-elasticities, but there is little theory as to why they would change and in which direction. With enough observations, Chow’s (1960) test can determine whether the slopes are stable pre- and post-entry. In our study, because of the small sample of observations in both datasets, we tested the stability of the parameters when the observations after an entry occurred were added (Maddala 1977) for each entry. The tests failed to reject the stability of the parameters pre- and post-entry, except in the case of brand C. However, given that the brand did not advertise, this brand’s advertising decisions could not be modeled in the rest of the analysis. Consequently, the effect of new competition is modeled parsimoniously as a "main" effect in the relevant brand models of market share.
COMPETITIVE REACTIONS TO MARKET ENTRY

where:

\[ m_i(t) = \text{market share of brand } i \text{ at time } t, \]
\[ a_i(t) = \text{advertising share of brand } i \text{ at time } t, \]
\[ D_k(t) = \text{dummy variable for entry of brand } A+ \text{ plus } (k = 1), \text{brand } F \text{ (} k = 2), \text{and brand } E \text{ (} k = 3), \]
\[ \beta \text{'s} = \text{response function parameters, and} \]
\[ u_i(t) = \text{disturbance term.} \]

Overall, the fits confirmed that the important variables were included (\( R^2 = .94, .97, .74, \text{ and } .92 \) respectively for brands A, B, C, and D, though they should be evaluated with caution given the relatively few degrees of freedom). The OLS estimation results indicated the importance of the lagged dependent variable for most of the brand models. However, variations across brands in the significance of the other parameters were observed. The lack of significance could be due to the inefficiency of the OLS estimation if the error terms are contemporaneously correlated (Beckwith 1972; Reibstein and Gatignon 1984). Consequently, the market share models were reestimated simultaneously as seemingly unrelated regressions to take into account possible correlations between the disturbance terms. Given that the OLS estimates are not efficient, a cutoff \( t \)-value of 1.2 was used for including each variable in the SUR model specification according to a procedure used by Schultz and Hanssens (1977) and Gatignon (1984). Further, the lagged market share coefficient for brand B was constrained to 1 because the unconstrained estimate of 1.033 (though not statistically different from 1) could lead to inconsistent market share results. This constraint did not significantly affect any of the other coefficients.

The results are summarized in Table 1. Advertising share is related significantly to the market share of the two largest brands, A and D. These coefficients (.068 and .136 for A and D, respectively) are in the typical range of advertising elasticities (Lambin 1976). It is noteworthy that the advertising of brand D is approximately twice as effective as the advertising of brand A, indicating substantial differences in firm abilities. In addition, the market leader, brand A, is the only brand negatively affected by the two entries of new competitors (.102 and -.078 for brands F and E, respectively). However, the brand A-plus product line extension had a positive effect on brand A’s share (.086). This additional share was taken from brand C (.133) and brand B (-.134). The positive effect of the brand E entry on brand C’s market share (.139) may be due to a difference in their positioning. Though both are second-generation formulations, brand E was launched as a relatively expensive, heavily advertised brand. Brand C’s positioning as a similar formulation but as a low priced national brand may have become clearer to the consumer as a result of the “splashy” entry of a physically similar brand. In other words, brand E may have increased awareness and acceptance of second-generation national brands; hence consumers may have been more willing to notice brand C’s price advantage and to “experiment” with another second-generation national brand (albeit an unadvertised name).

Finally, the lagged market share coefficients of brand B’s share (not significantly different from 1.0 and constrained to that value), combined with the negative constant term (-.068), reflect the smoothly declining share trend of the brand. Brand A and brand C have relatively low values for lagged share (.369 and .385, respectively), indicating that these two brands are more volatile and need advertising to support their share. Brand D benefits from a relatively strong stability (with a lagged market share coefficient of .725), in addition to the strong impact of advertising.

By the same procedure, the market share model for each airline is represented by equation 2.

\[
\begin{align*}
\tilde{m}_i(t) &= e^{\beta_0}m_i(t - 1)\tilde{f}(t)\tilde{a}_i(t)\tilde{p}_i(t)e^{\beta_0}D_i(t)
\end{align*}
\]

where:

\[ m_i(t) = \text{market share of airline } i \text{ at time } t, \]
\[ a_i(t) = \text{advertising share of airline } i \text{ at time } t, \]
\[ f(t) = \text{share of number of flights of airline } i \text{ at time } t, \]
\[ p_i(t) = \text{price of airline } i \text{ relative to average price on the route at time } t, \]
\[ D_i(t) = \text{dummy variable for entry of airline } 4, \]
\[ Q_2(t), Q_3(t), Q_4(t) = \text{quarterly dummy variables}, \]
\[ \beta \text{'s} = \text{response function parameters, and} \]
\[ u_i(t) = \text{disturbance term.} \]

Table 1

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Brand A</th>
<th>Brand B</th>
<th>Brand C</th>
<th>Brand D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.108</td>
<td>-1.908</td>
<td>1.570</td>
<td>.398</td>
</tr>
<tr>
<td>Lagged share</td>
<td>.006</td>
<td>-1.033</td>
<td>NA</td>
<td>.136</td>
</tr>
<tr>
<td>Advertising share</td>
<td>.068</td>
<td>-1.014</td>
<td>NA</td>
<td>(.359)</td>
</tr>
<tr>
<td>Brand A plus</td>
<td>.086</td>
<td>-1.033</td>
<td>-1.033</td>
<td>—</td>
</tr>
<tr>
<td>Brand F entry</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Brand E entry</td>
<td>.078</td>
<td>—</td>
<td>.139</td>
<td>—</td>
</tr>
<tr>
<td>Number of observations</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>( R^2 ) (based on OLS)</td>
<td>.94</td>
<td>.97</td>
<td>.74</td>
<td>.92</td>
</tr>
</tbody>
</table>

\(^a\)-statistics are in parentheses. Variables with \( t \)-values less than 1.2 in OLS estimation are omitted and indicated by a dash; NA indicates no advertising for the brand.

\(^b\)Coefficient constrained to 1.0.
As is similar to the fit obtained in the OTC-gyn market, the independent variables explain respectively 98.5, 97.7, and 98.2% of the variances in market share for the three airlines. The seemingly unrelated regression estimation results are reported in Table 2 (variables for which the OLS coefficient estimates had a t-value inferior to 1.2 are eliminated).

In this market, as typically found, the number of flights is the strongest determinant of market share, with share elasticities of .905, .907, and .880 for each airline, respectively. Advertising share is not significant, but the relative price of airline 3 has a significant impact on its market share (with an elasticity of -.185). Though the lagged share variable was eliminated after the OLS results showed insignificance, the market shares of airlines 1 and 2 have a significant seasonal component. Both airlines 1 and 3 are affected significantly by the entrant. The national airline, 3, was hardest hit (-.187), whereas the regional airlines were affected less (-.066 for airline 1). In fact, airline 2’s market share increased after the entry, everything else being constant. Its sales (i.e., the number of passengers), however, were affected negatively by the entry.

To this point we have estimated the effectiveness of each competitor’s marketing mix variables. We also have established that, in the OTC-gyn market, the two new competitors and the product line extension had a discernible impact on the leader’s share of the market. The impact was similar in the airline market. We now test our propositions via the estimation of decision models, which represent the advertising and number-of-flights levels (for the OTC-gyn and airline markets, respectively) chosen by each competitor before and after entries.

Marketing decision equations. The decision variable to be modeled is the advertising expenses in the OTC-gyn market. In the airline market, only the number of flights is considered because this marketing decision variable is significantly more important than price or advertising, as discussed before. The specification of decision models is made difficult by the complexity of the phenomena to incorporate. The decision equation must incorporate interfirm coordination of mix variables and reactions to competitors, both with lags in reactions and anticipation of competitors’ actions. Hanssens (1980) discusses the modeling of these issues and proposes a method based on time series analysis to assess empirically the correct model specification. However, with this method one must assume the availability of a substantial number of observations to consider all cross (leads and lags) correlations.

The method we used is similar in spirit, though the limited sample period did not enable us to use time series analysis. Instead, we considered all leads and lags in a stepwise manner, each step introducing a set of variables entered in a stepwise regression (forward). In the first step, the marketing mix of one brand was specified as a function of all other brands’ marketing mix with lags and leads of one and two periods. Only variables with t-statistics greater than 1.2 were retained for the second step by the same procedure as described before. In that second step, the competitive entry dummy variables were introduced. For the OTC-gyn market, where multiple entries occurred, only the current value of the dummy for the entry of brand E was specified, whereas up to two-period leads and lags were specified and entered stepwise for the entry of brand F. Brand A-plus was not included with a dummy variable, as it is not a new brand. The reactions to brand A’s total advertising are already modeled in step one of the procedure. In a final step, the variables that had been entered were forced into the model and the leads and lags for the last entry (brand E) were investigated in a forward stepwise regression. This procedure was followed for each brand that advertised (i.e., A, B, and D). The homogeneity (pre/post entries) for the coefficients of the decision equations was established by testing the stability of the parameters when new observations were added (Maddala 1977). All the tests proved insignificant in both datasets.

This procedure led to the following specification of the model for each brand in the OTC-gyn market.

\[
A_i(t) = e^{a_i + a_{i}A_i(t-2) + a_{i}A_i(t-2) + a_{i}e^{d_{i}(t-2)}}e^{d_{i}(t)}
\]

where:

\[
A_i(t) = \text{advertising expenditures at time } t \text{ for brand } A \quad (i = 1), \text{ brand } B \quad (i = 2), \text{ and brand } D \quad (i = 4),
\]

Table 2

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Airline 1</th>
<th>Airline 2</th>
<th>Airline 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>.428</td>
<td>.371</td>
<td>1.290</td>
</tr>
<tr>
<td></td>
<td>(.94)</td>
<td>(1.29)</td>
<td>(2.76)</td>
</tr>
<tr>
<td>Lagged share</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Advertising share</td>
<td>—</td>
<td>.011</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of number of flights</td>
<td>.905</td>
<td>.907</td>
<td>.880</td>
</tr>
<tr>
<td></td>
<td>(21.52)</td>
<td>(10.57)</td>
<td>(13.55)</td>
</tr>
<tr>
<td>Relative price</td>
<td>-.035</td>
<td>—</td>
<td>-.185</td>
</tr>
<tr>
<td></td>
<td>(.40)</td>
<td></td>
<td>(2.38)</td>
</tr>
<tr>
<td>Entry</td>
<td>-.066</td>
<td>.125</td>
<td>-.187</td>
</tr>
<tr>
<td></td>
<td>(2.44)</td>
<td>(2.86)</td>
<td>(3.18)</td>
</tr>
<tr>
<td>Quarter 2</td>
<td>.045</td>
<td>-.073</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(2.04)</td>
<td>(2.26)</td>
<td></td>
</tr>
<tr>
<td>Quarter 3</td>
<td>—</td>
<td>-.061</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(1.98)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarter 4</td>
<td>.016</td>
<td>-.041</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(.68)</td>
<td>(1.53)</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>23</td>
<td>23</td>
<td>23</td>
</tr>
<tr>
<td>R² (based on OLS)</td>
<td>.985</td>
<td>.977</td>
<td>.982</td>
</tr>
</tbody>
</table>

*t-statistics are in parentheses. Variables with t-values less than 1.2 in OLS estimation are omitted and indicated by a dash.
COMPETITIVE REACTIONS TO MARKET ENTRY

\[
D(k) = \text{value of entry dummy at period } t \text{ for brand } F \quad (k = 2) \text{ and brand } E \quad (k = 3) \text{ (value is 0 before entry and 1 after entry)}
\]

\(\alpha's = \text{reaction function coefficients, and } \epsilon(t) = \text{disturbance term.}
\]

Given this model specification with simultaneity of decisions, we estimated the advertising decision model by three-stage least squares. Table 3 reports the results. Brand B shows the largest reactions to both brand A’s and brand D’s advertising (reaction elasticities are 5.639 and 4.21, respectively) with a lag of one quarter in relation to brand D advertising. Brand A reacts relatively strongly to brand D’s advertising (.329), whereas it avoids face-to-face competition with B (the small but negative reaction elasticity is \(-.028\)). Both reactions occur with a two-quarter lag. Brand D seems to make its advertising decisions independently of its competitors.

These reaction coefficients (elasticities) demonstrate the asymmetry of competitive behavior. The estimates of the coefficients indicate that brands A and B reacted to F’s entry by increasing their level of advertising expenditures (.794 for A and 5.767 for B). The negative coefficient for the effect of F’s entry on the advertising level of D (\(-1.329\)) may reflect a decision to reallocate resources across brands within the manufacturer’s portfolio. In contrast, in reaction to brand E’s entry, D increased its advertising expenditures (.845) whereas B decreased its expenditures (\(-11.78\)) and A did not react. The purpose of our study is to explain the diversity of these reactions. It is interesting to note before proceeding, however, that brand A anticipated F’s entry and brand D anticipated E’s entry (both lead two quarters).\(^4\) They both increased their advertising expenditures before the entries. Table 1 also shows that D’s market share was not affected by E’s entry, whereas F’s entry had a negative effect on A’s share. These outcomes can be explained partly by the competitive response anticipation and by the fact that D’s advertising elasticity is much larger than A’s.

For the airline data, the flight decision model resulting from the analysis is shown in equation 4.

\[
F(t) = \epsilon(t) = P(t) = \text{price of airline } i \text{ at time } t \quad (i = 1, 2, 3),
\]

\[
F(t) = \frac{\text{number of flights of airline } i \text{ at time } t}{A(t) = \text{advertising expenditures at time } t,}
\]

\[
D(t) = \text{dummy variable for entry of airline } 4,
\]

\(\alpha's = \text{reaction function coefficients, and } \epsilon(t) = \text{disturbance term.}
\]

The three-stage least square estimation results are given in Table 4. The interpretation of the results is straightforward. For competitive behavior in general, airline 1 seems to compete directly with airline 2, which has the highest market share. When airline 2 decreases its price or increases its advertising, airline 1 (with the second largest share) reacts by increasing its number of flights (\(-.890\) and \(.150\)). Airline 1 has the opposite competitive behavior in relation to airline 3. In response to airline 3’s decrease in price, increase in advertising, or increase in flights, airline 1 decreases its number of flights (\(.825\), \(-.178\), and \(-.464\)), suggesting a “cooperative” behavior with airline 3 against the leader.

Airline 2 avoids competing in reaction to advertising changes by its competitors. However, it has a tendency (\(\alpha = .145\)) to react to increases in the number of flights of airline 2, though the coefficient is not statistically significant. Further, airline 2 offers more flights when its rivals raise their prices (.392 and .380).

---

\(^4\)Interviews of brand A managers (postanalysis) confirmed that brand F’s entry was expected and advertising was boosted before entry in anticipation of the new competition.

---

Table 3

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Brand A</th>
<th>Brand B</th>
<th>Brand D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.173</td>
<td>-60.522</td>
<td>5.963</td>
</tr>
<tr>
<td>(3.73)</td>
<td></td>
<td>(3.39)</td>
<td>(71.78)</td>
</tr>
<tr>
<td>Brand A advertising</td>
<td>- .028</td>
<td>5.639</td>
<td>-</td>
</tr>
<tr>
<td>(1.72)</td>
<td></td>
<td>(3.60)</td>
<td></td>
</tr>
<tr>
<td>Brand B advertising</td>
<td>- .028</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>(1.72)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand D advertising</td>
<td>.329</td>
<td>4.21</td>
<td>-</td>
</tr>
<tr>
<td>(1.78)</td>
<td></td>
<td>(1.788)</td>
<td></td>
</tr>
<tr>
<td>Brand F entry dummy</td>
<td>.794</td>
<td>-1.329</td>
<td>.845</td>
</tr>
<tr>
<td>(4.62)</td>
<td></td>
<td>(2.05)</td>
<td>(3.17)</td>
</tr>
<tr>
<td>Brand E entry dummy</td>
<td>-</td>
<td>-11.78</td>
<td></td>
</tr>
<tr>
<td>(3.71)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Numbers in parentheses are t-statistics; \(L = n\) means a lead of \(n\) periods and \(l = n\) means a lag of \(n\) periods.
Table 4
MODEL OF NUMBER OF FLIGHTS: THREE-STAGE LEAST SQUARE ESTIMATION RESULTS

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Airline 1</th>
<th>Airline 2</th>
<th>Airline 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>8.640</td>
<td>1.69</td>
<td>9.061</td>
</tr>
<tr>
<td>Price, airline 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Price, airline 2</td>
<td>-</td>
<td>1.50</td>
<td>-</td>
</tr>
<tr>
<td>Price, airline 3</td>
<td>-</td>
<td>.925</td>
<td>-</td>
</tr>
<tr>
<td>Advertising, airline 2</td>
<td>.150</td>
<td>-</td>
<td>.073</td>
</tr>
<tr>
<td>Advertising, airline 2(lagged)</td>
<td>.054</td>
<td>-</td>
<td>(1.88)</td>
</tr>
<tr>
<td>Advertising, airline 3</td>
<td>-.178</td>
<td>-.145</td>
<td>-</td>
</tr>
<tr>
<td>Number of flights, airline 1</td>
<td>-.464</td>
<td>-</td>
<td>(2.65)</td>
</tr>
<tr>
<td>Number of flights, airline 3</td>
<td>-.225</td>
<td>.239</td>
<td>-.459</td>
</tr>
<tr>
<td>Entry dummy</td>
<td>-.225</td>
<td>.429</td>
<td>-4.59</td>
</tr>
</tbody>
</table>

*Numbers in parentheses are t-statistics.

Airline 3 shows a somewhat less generalizable behavior. It competes with airline 1 by increasing its number of flights in response to a price cut of airline 1 (—.425), but by “cooperating” in response to a change in the number of flights (—.310). Airline 3 responds only to airline 2’s change in advertising expenses (.073).

The results pertaining to new entry show that airline 2, with the highest number-of-flights elasticity, reacted to the entrant by increasing its number of flights (.239), but the other two competitors decreased theirs (.225 and —.459).

This analysis of competitive responses shows that reactions in general and reactions to a new entry differ by competitor. An explanation for these differences was tested empirically in the two markets studied.

Hypotheses

Our principal interest is the coefficients of the dummy variables in the reaction function equations (3 and 4 respectively for each market), which represent changes in advertising expenditures by firm i in response to the new entry or entries. These coefficients are the \( \alpha_{k1} \)'s and \( \alpha_{k4} \)'s in the OTC-gyn market and the \( \alpha_{k1} \)'s in the airline market. Corresponding to the propositions, the following hypotheses can be formulated in terms of the model parameters.

Expressing \( \alpha_k \) (with \( k = 3,4 \) for the OTC-gyn market and \( k = 7 \) for the airline market) as a process function (where \( \alpha_{k1} \) represents the reactions to the entry of brand F, \( \alpha_{k4} \) represents the reactions to the entry of brand E, and \( \alpha_{k7} \) represents the reactions to the entry of airline 4), \(^5\)

\[ \alpha_k = \gamma_{0k} + \gamma_{1k} \beta_k \]

enables us to express the following hypotheses.

\[ H_1: \gamma_{0k} < 0 \]

\[ H_2: \gamma_{1k} > 0 \]

\( H_1 \) expresses the idea that firms retreat (\( \alpha_{k1} < 0 \)) with an inelastic market instrument (when \( \beta_k \) is small) and attack (\( \alpha_{k1} > 0 \)) with an elastic instrument (when \( \beta_k \) is large). In this case, the marketing instrument is advertising for the OTC-gyn market and the number of flights for the airline market. In other words, if elasticity is low, the intercept term \( \gamma_{0k} \) dominates. We expect \( \gamma_{0k} \) to be negative, indicating negative reaction with a low elasticity instrument (H1). As elasticity grows, the \( \gamma_{1k} \) term (positive by H2) dominates, indicating positive reaction. These two hypotheses also contain the idea that there is a medium range of elasticity where no reactions can be expected (P2). Therefore, the two research hypotheses completely cover the three theoretical propositions stated before.

Results. For the OTC-gyn market, the advertising decision model (3) was reestimated with the constraint on the coefficients as hypothesized. The process function was not applied to the brand F entry dummy coefficient for brand D (\( \alpha_{D4} \)) because both brands are marketed by the same company. Consequently, the coefficient does not have a competitive interpretation, but instead represents the reallocation of company resources to multiple products.\(^6\) Therefore, constraining the coefficient (\( \alpha_{D4} \)) to a process representing a competitive rationale would be invalid. The process function constraints are applied across equations. The estimation was carried out by using the TSP procedure LSQ, which applies to our case of simultaneous equations with linear constraints across equations.

Table 5 shows the estimates of the parameters of the advertising decision functions for the OTC-gyn market, including estimates of the coefficients of the linear constraint, which constitute our hypothesis test. The signs

\(^5\)The process function does not contain an error term; the EGLS estimate that would result has unknown properties given the small cross-sectional sample, because the EGLS estimator is only more efficient asymptotically. A specification without an error term in the process function actually provides a stronger test of the hypothesis, because the estimator is asymptotically less efficient.

\(^6\)The rationale of our propositions applies to the direction and extent of competitive reaction, and not the speed of reaction. It is clear from Table 3 that A1’s reaction to F’s entry and D’s reaction to F’s entry were faster (even before the entries occurred) than B’s reaction. Brand D’s coefficient representing changes in its advertising expenditures due to brand F’s entry is contemporaneous with the entry, as it reflects the portfolio planning of the company marketing both brands. Though the speed of reaction is an important dimension of reaction (Heil 1987), its analysis is beyond the scope of our article. Therefore, the constraints represented by the process function were applied similarly to all reactions due to an entry, regardless of the speed of the reaction. The assumption is that the explanation represented by the constraints does not distinguish whether the reaction is fast or slow.
Table 5
ADVERTISING DECISION MODEL IN OTC-GYN MARKET WITH PROCESS EQUATIONS

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Brand A</th>
<th>Brand B</th>
<th>Brand D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.517</td>
<td>-63.737</td>
<td>5.968</td>
</tr>
<tr>
<td></td>
<td>(2.69)</td>
<td>(2.98)</td>
<td>(58.37)</td>
</tr>
<tr>
<td>Brand A advertising</td>
<td>—</td>
<td>5.211 (l = 1)</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.63)</td>
<td></td>
</tr>
<tr>
<td>Brand B advertising</td>
<td>-.025 (l = 2)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand D advertising</td>
<td>.044 (l = 2)</td>
<td>5.234</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(2.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand F entry dummy</td>
<td>-3.575 + 61.48 β₁₂</td>
<td>-1.513</td>
<td>(1.71)</td>
</tr>
<tr>
<td></td>
<td>(1.71)</td>
<td>(2.05)</td>
<td></td>
</tr>
<tr>
<td>Brand E entry dummy</td>
<td>-1.042 + 16.23 β₁₂</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.62)</td>
<td>(2.37)</td>
<td></td>
</tr>
</tbody>
</table>

Where (from Table 1):

β₁₂ = .067
β₁₃ = 0
β₁₄ = .137

*Numbers in parentheses are t-statistics; l = n means a lag of n periods.

and magnitude of the coefficients of the linear constraint on the new entry dummy variables, boxed in Table 5, support H₁ and H₂. Coefficients γ₀ₖ are negative (-3.575 and -1.042 respectively for the entries of brand F and brand E) and coefficients γ₁ₖ are positive (61.48 and 16.23 respectively).

These findings indicate that brands for which advertising has little impact on market share (β₁₂ is low) react to the entry by decreasing their advertising expenditures. This reaction is in accord with the idea that firms do not fight with weapons that are not highly effective. However, as brand advertising elasticity (β₁₂) increases, firms cut back by smaller increments (αₖ grows larger as the γ₀ₖβ₁₂ term compensates for the negative impact of γ₀ₖ). Eventually, the reaction turns positive. For brand F, the turning point is at β₁₂ = .0581; for greater elasticities, the reaction is positive. For brand E, reactions turn positive for firms whose advertising elasticity is greater than .0642. These results apply to the brands in this market across two entries. Though it does not involve many entries and many brands, the model is estimated simultaneously with all the data in the sample across brands and time. Consequently, model parameters are estimated with relatively large statistical power.

By the same procedure, the airline analysis provides a replication of the OTC-gyn market. Table 6 indicates that the coefficients support our hypothesis. The γ coefficients are both statistically significant with the expected sign (γ₀₁ = -23.08, γ₁₁ = 25.65).

This finding indicates that firms whose flight decisions affect their own sales very little (β₂₃ is low) react to the new entry by decreasing their market effort (number of flights), in accord with the idea that firms do not fight with weapons that are not highly effective. However, as flight elasticity (β₂₃) increases, firms cut back by smaller increments (αₖ grows larger as the γ₀₃/β₂₃ term increases).

Table 6
NUMBER-OF-FLIGHTS DECISION MODEL WITH PROCESS EQUATIONS

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Airline 1</th>
<th>Airline 2</th>
<th>Airline 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>5.896</td>
<td>1.318</td>
<td>7.950</td>
</tr>
<tr>
<td></td>
<td>(5.80)</td>
<td>(2.20)</td>
<td>(5.85)</td>
</tr>
<tr>
<td>Price, airline 1</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>(1.66)</td>
<td>—</td>
</tr>
<tr>
<td>Price, airline 2</td>
<td>-.933</td>
<td>.501</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(6.43)</td>
<td>(3.86)</td>
<td></td>
</tr>
<tr>
<td>Price, airline 3</td>
<td>.905</td>
<td>.336</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(6.53)</td>
<td>(2.55)</td>
<td></td>
</tr>
<tr>
<td>Advertising, airline 2</td>
<td>.138</td>
<td>—</td>
<td>.055</td>
</tr>
<tr>
<td></td>
<td>(5.13)</td>
<td></td>
<td>(1.42)</td>
</tr>
<tr>
<td>Advertising, airline 2</td>
<td>.048</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>(lagged)</td>
<td>(1.90)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising, airline 3</td>
<td>-.150</td>
<td>—</td>
<td>-.100</td>
</tr>
<tr>
<td></td>
<td>(3.82)</td>
<td></td>
<td>(1.88)</td>
</tr>
<tr>
<td>Number of flights,</td>
<td>—</td>
<td>.168</td>
<td>—</td>
</tr>
<tr>
<td>airline 1</td>
<td></td>
<td>(1.81)</td>
<td></td>
</tr>
<tr>
<td>Number of flights,</td>
<td>-.0001</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>airline 3</td>
<td>(0.0008)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Where (from Table 2):

β₁₂ = .090
β₂₃ = .907
β₃₄ = .880

*Numbers in parentheses are t-statistics.
compensates for the negative impact of $\gamma_{10}$. The turning point from negative to positive reaction occurs for flight elasticity greater than .90; beyond that point, firms retaliate against the entrant by offering more flights.

**DISCUSSION AND CONCLUSION**

Our results offer some support of the hypotheses proposed. In two unrelated oligopolistic markets, we observe considerable variation in reaction to three entries. The effectiveness of the major marketing instruments—advertising expenditures and number of flights for OTC-gym and airlines, respectively—is shown to predict how competitors react to a new entry: that is, whether they increase or decrease their efforts. In accord with the literature on competitive behavior, we find that firms react positively to entrants (by retaliation or counterattack) with their effective weapons, where "effective" means having relatively large elasticity. Also consistent with the literature, firms cut back (withdraw) their inelastic marketing mix instruments. Undoubtedly many factors influence a competitor's reaction. Nonetheless, our results suggest that reactions can be better understood and predicted by observing one factor: the effectiveness of a current competitor's marketing mix instruments.

The contribution of our study is to suggest when a positive reaction with a marketing instrument will be observed and when a negative reaction will be observed instead. The criterion, elasticity, is relatively easy to measure and conforms with extant theory in industrial organization and strategic marketing. The ideas expressed here are very general; they can be applied to various marketing mix instruments and to multiple scenarios. We consider response to the entry of a new product, but one could substitute, for example, the repositioning of a current brand. Repositioning, if successful, operates much as does an entry by changing the competition set. Other competitors may react by either increasing or decreasing their marketing effort, depending on the effectiveness of that effort.

Our study has certain limitations. First, in both industries studied, elasticities were not significantly altered by the entrant. In other settings, an entrant may shift elasticities of competitors, thereby affecting their reactions and complicating the prediction of competitive response. Second, inferences that can be made from modeling one industry are necessarily limited to that industry. The model is merely a summarizing of the data evidence. It is the nature of scientific research that knowledge progresses by convergent studies and replications (Zaltman, Pinson, and Angelmar 1973). We provide such a replication by testing our hypothesis in two industries. Nevertheless, more replications are necessary for generalization.

Methodologically, given the limited data, any significance at the usual confidence level provides a strong rejection of the null hypothesis of no effect. Nonetheless, the small sample size does limit the scope of the effects that can be observed and measured. A natural progression of our research therefore would be to increase the number of explanatory variables in order to yield a wider explanation of competitive moves and countermoves. For example, environmental uncertainty may affect response, perhaps blunting reactions or even leading firms not to react. Another consideration may be the firm's impression of the entrant's capabilities. A firm may react strongly to an entrant judged to be capable and may not react to another entrant regarded as a minor threat. Further research also is needed to establish the generalizability of the ideas developed here, which are a step toward a more complete theory of competitive actions, in particular as it discriminates between current competitors' reaction strategies. Nevertheless, our study does present an explanation, with empirical support in two industries, for observable differences in firms'/brands' reaction patterns to entries of new competitors in the market. As such, the study enhances our understanding of a complex and crucial strategic issue—the pattern of competitive rivalry.

**REFERENCES**


Graham, David R., Daniel P. Kaplan, and David S. Sibley (1981), "Efficiency and Competition in the Airline Indus-


