NEW BRAND POSITIONING AND PRICING IN AN OLIGOPOLISTIC MARKET

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The positioning and pricing of a new brand requires knowledge about the relationship of both demand and cost with potential attribute locations and prices. This paper addresses this problem and illustrates it in the context of the automobile market. Multi-attribute expected utility theory which allows for consumer uncertainty about the brands is used to model individuals' behavior. Attribute weights are estimated from market survey data on brands' attributes and preferences using LINMAP as an estimation procedure. Expected utility is then updated using the multinomial logit model and choice data to account for the observation that stated preferences do not perfectly reflect the eventual choice. It is hypothesized that, when faced with an actual choice, price may become more important to the consumer, while other attributes may become more or less important than is reflected in stated preferences. The resulting estimated choice probabilities are aggregated to form demand functions facing each brand which depend on all brands' prices and attribute space locations. Assuming there is a price equilibrium in the existing market and that firms have the same variable cost function, variable costs as a function of a brand's attribute levels are estimated. Given the demand and cost functions facing each firm including the potential new entrant, the profit maximizing positioning and pricing of a new brand is analyzed using a game theoretic approach. A solution is sought under the assumption that incumbents react to entry by changing their prices. Possible approaches to the translation of the perceptual attribute positioning of the new brand to physical and engineering attributes are reviewed. Improvements and future extensions of the study are discussed.

(Positioning; New Products)

Introduction

The choice of an attribute space specification and price for a new brand is one of the most important, yet difficult decisions made by a firm. To execute this correctly a firm needs to know consumers' demand for attributes, the cost of supplying these attributes and the potential reactions of existing competitors.

Research and Development groups and creative individuals have been frequent originators of new product concepts. However, in the last decade analytical approaches to aid in the positioning problem have been proposed in the academic literature and have found increasing application in firms' decisions (e.g., Oren, Rothkopf and Smallwood 1980; Page and Rosenbaum 1987). Different aspects of the positioning problem have been addressed in the academic literature. Consumer demand for attributes or the estimation of a multi-attribute utility function has been addressed in many marketing studies using a variety of estimation techniques (e.g., Green and Rao 1971; Carroll 1972; Beckwith
and Lehman 1973; Srinivasan and Shocker 1973; Punj and Staelin 1978). A monopolist’s profit maximizing product line decisions have been investigated from a theoretical point of view by Moorthy (1984) and from a practical point of view by Green and Krieger (1985) and Dobson and Kalish (1988). A multi-attribute framework which encompasses consumers and multiple producers has been proposed in the economics literature by Lancaster (1966). Hauser and Simmie (1981) and Bachem and Simon (1981) study the positioning of a new brand in an existing market where incumbents do not react. Reaction by an existing competitor to an entrant within the Lancaster framework has been addressed by Hauser and Shugan (1983). Hauser (1988) and Moorthy (1988) investigate, using a game theoretic framework, equilibrium in oligopolistic markets. A perfectly competitive multi-attribute market with a continuum of brand offerings is modeled by Rosen (1974). His model specifies costs as a function of attributes and has been applied to the automobile market by Agarwal and Ratchford (1980).

Computational solutions for the oligopolistic positioning problem have been offered by Gavish, Horsky and Srikanth (1983) and Sudharshan, May and Shocker (1987). They both study the case in which consumers have finite ideal points on attributes and incumbents do not react. These solution procedures ignore pricing and cost issues, thereby concentrating in essence on the identification of an attribute space location which would attract the largest market share. Presumably, promising locations would then be further investigated and their costs and optimal prices determined. Johnson (1987) and Dodson and Brodsky (1987) in their commentaries on the Sudharshan, May and Shocker paper point to costs and competitive reactions as two important shortcomings of the existing empirical works. A comprehensive review of the positioning literature is provided by Schmalensee and Thiss (1988).

In this paper we address the problem of identifying the profit maximizing price and attribute positioning of a new brand in an oligopolistic market where competitors do react to entry. In particular, we concern ourselves with those common situations where consumers have infinite ideal levels for each attribute. In this case one needs to investigate both the demand for and cost of supplying each attribute prior to pursuing the positioning problem. If costs and prices are of no concern then it is clearly optimal for the producer to provide as much as possible of each attribute at a low price. A new brand of this type presumably will be chosen by all. In comparison to the above cited works we (i) incorporate uncertainty into the preference based estimation of the multi-attribute model; (ii) combine individual level preference estimates with cross-sectional data on choices to provide an “updated” choice function; (iii) recover a multi-attribute cost function from observed prices in an oligopolistic market; and (iv) determine equilibrium location and price for an entrant in a market in which incumbent firms react on prices and profits are maximized.

In the next section we formulate and estimate the consumer’s multi-attribute preference and choice models and devise the aggregate demand function facing each firm including the entrant. In the following section we model and estimate a multi-attribute cost function. Having both the demand and cost functions we derive in the next section a profit maximizing price and attribute positioning for a new brand. Much remains to be done in this very complex problem area and we therefore conclude with a detailed discussion of potential improvements on the methodology and issues for future research.

**Consumer Choice and Aggregate Brand Demand**

The consumer is considered to make choices with imperfect information about the existing brands. In other words, he is uncertain about their quality. Consequently, expected utility theory is used to model the formation of his preferences. The multi-attribute expected utility function used includes the perceived attribute levels of the brands, their
prices, the consumer's uncertainty about each brand and his income. We then allow for the possibility that consumers in their stated preferences may over-weight or under-weight the importance of price and the attributes and, therefore, these preferences do not correspond perfectly with choice. We allow for an updating of the importance of the attributes and price and derive an aggregate demand function facing each brand.

**Multi-Attribute Expected Utility**

We are interested in the formation of a consumer's preferences towards high priced, infrequently purchased durable brands. Since the income constraint and, thus, tradeoffs with the consumption of brands in other product categories is of importance in such a situation, a utility framework similar to the one used by Rosen (1974) is well suited for our purpose. The consumer problem in this framework is to identify in an $M$ brand market that brand for which:

$$\max_{m \in M} U(z_m, \text{AOG})$$

s.t. \( \nu R(z_m) + \text{AOG} \leq Y \), \hspace{1cm} (1)

where \( z_m \) is a $J$-dimensional vector of the attributes of brand $m$ and AOG is a conglomerate good representing the quantity of all other goods. The price of each unit of AOG is assumed to be one dollar. \( R(z_m) \) is the price of brand $m$ and $Y$ is the consumer's yearly household income. A high priced, infrequently purchased durable, such as a car, generally is purchased on an installment plan with a yearly interest rate of $\rho$ and a repayment period $\tau$. As a result, the yearly payment equals a fraction \([\rho/(1 + (1 + \rho)^{-\tau})]\) = $\nu$ of the total price.

The consumer problem also can be written as an unconstrained maximization:

$$\max_{m \in M} U(z_m, Y - \nu R(z_m))$$ \hspace{1cm} (2)

Since higher quality brands are likely to have higher prices, it is evident from equation (2) that the consumer trades off between the different attributes as well as between the attributes and all other goods. In this framework, unlike that of Lancaster (1966), the income effect is modeled in addition to the price effect.

The consumer may not have perfect information about the brands in his choice set. This necessitates the incorporation of uncertainty and risk into the preference formation process. We consider consumer uncertainty about each brand's overall value, \( V(z, Y - \nu R) \). This results in each brand's overall value being described by a distribution over its possible levels. This means that the individual's utility, \( U = f(V) \), for each brand is also uncertain. Consequently, the consumer maximizes expected utility, \( \mathbb{E}[U(z, Y - \nu R)] \), rather than utility. Earlier studies incorporating consumer uncertainty about brands include Hauser and Urban (1979), Meyer (1981), Wiggins and Lane (1983), Ratchford and Haines (1984) and Roberts and Urban (1988).

The functional form of the utility function and, consequently, its expected value needs to be determined. Bell and Raiffa (1979) show that if $V$ is interval scaled, the individual conforms to the von Neumann-Morgenstern axioms and $U = f(V)$ exists, then $U$ shows constant absolute risk aversion (as defined by Pratt 1964) with respect to $V$. This means the utility function is either linear ($U = a + bV$) or negative exponential ($U = a - b \exp\{-rV\}$) with respect to $V$. Empirical evidence concerning goodness of fit favors the negative exponential form (Currim and Sarin 1984). In addition, the linear model has the unappealing characteristic that the consumer's behavior is neutral regarding risk. Consequently, we use the negative exponential functional form,

$$U = a - b \exp\{-rV\},$$ \hspace{1cm} (3)

where $r > 0$ is the absolute risk aversion measure. If $V(z, Y - \nu R)$ is normally distributed,
\[ E[U(z, Y - vR)] = a - b \exp \{ -r(E[V(z, Y - vR)] - \frac{1}{2}rs^2) \}, \tag{4} \]

where \( s^2 \) is the variance of the brand’s overall value. Since expected utility is ordinal, maximization of equation (4) is equivalent to maximization of \( E[V(z, Y - vR)] - \frac{1}{2}rs^2 \).

Appendix A specifies two groups of models. The first group incorporates consumer uncertainty about the overall values of the brands and the second assumes consumer certainty. In each group several functional forms are specified. An empirical evaluation will determine if incorporating uncertainty improves the ability to predict preferences and the functional form to be used in this study. The empirical evaluation will be conducted using survey results in which each respondent provides a rank ordering of preferences for a set of brands (for which list prices are given), their perceptions of these brands’ attribute levels, their uncertainty about the brands and their income. Once a functional form has been chosen and each consumer’s parameters estimated, each consumer’s expected utility towards existing and new brands can be predicted.

**From Preference to Choice**

The expected utilities estimated based on stated preferences may not reproduce the preference ranking perfectly. Measurement errors enter, not all attributes are considered, attribute perceptions are not elicited perfectly, etc. Moreover, the stated preferences themselves may not predict actual choices perfectly. For example, Juster (1966) and Morrison (1979) provide evidence that consumers’ stated “intentions to buy” far from correlate perfectly with actual behavior. Two possible reasons for this deviation may be that the price being offered at the outlet is different than the one specified in the questionnaire and that when faced with an actual choice consumers change the relative importance of the attributes and price. In particular, in making a choice in an expensive product class, consumers may weight price (more precisely, the consumption of all other goods) more heavily than is reflected in their stated preferences. Similarly, other attributes may become more or less important. Such updating is likely to be less pronounced in frequently purchased product classes where it is performed by the consumer on a frequent basis.

All this implies that the expected utility of brand \( m \) at time of choice equals

\[ E(U_{m}^{true}) = \alpha E(U_{m}^{predicted}) + \sum_{j=1}^{J+1} \beta_j f(z_{jm}) + \epsilon_m = E(U_{m}^{updated}) + \epsilon_m, \tag{5} \]

where \( \alpha \) and the \( \beta_j \)’s are updating coefficients, \( f(\quad) \) is a function to be specified and \( \epsilon_m \) is an error which results from measurement errors and random events which occur at time of choice. For simplicity above and hereafter, all other goods is treated as a \( J + 1 \) th attribute. However, \( z \) will continue to represent only the \( J \) attributes. \( E(U_{m}^{predicted}) \) is the predicted expected utility of brand \( m \) based on the expected utility function estimated using stated preferences. It should be noted that the attribute levels and actual market price of brand \( m \) are considered in \( E(U_{m}^{predicted}) \) as well as in the updating terms.

Thus, if what we have is the predicted (computed) expected utility of each brand, then the probability that the consumer will choose brand \( m \) over brand \( k \) is

\[ P(m > k) = P[E(U_{m}^{true}) > E(U_{k}^{true})] \]

\[ = P[E(U_{m}^{updated}) + \epsilon_m > E(U_{k}^{updated}) + \epsilon_k] \]

\[ = P[E(U_{m}^{updated}) - E(U_{k}^{updated}) > \epsilon_k - \epsilon_m]. \tag{6} \]

\(^1\) Further discussion of the assumptions leading to equation (4) is provided in Roberts and Urban (1988).
If the error term $\epsilon_m$ for all $M$ brands considered has a Gumbel distribution, then the probability that $m$ will be chosen over all other brands is

$$P(m) = \frac{\exp\{E(U_m^{\text{updated}})\}}{\sum_{M}^{M} \exp\{E(U_j^{\text{updated}})\}}. \tag{7}$$

Equation (7) is the multinomial logit model. The parameters $\alpha$ and $\beta_j, j = 1, 2, \ldots, J + 1$, of equation (5) can be estimated using equation (7) and data on consumers’ actual choices and prices paid.

**Estimation and Testing of Consumers’ Preference and Choice Processes**

To evaluate empirically the consumer choice processes modeled above we collected data in early 1985 on consumers’ evaluations and choices of cars. We concentrated on mid-sized and priced sporty sedans. Through a phone survey and personal interviews we determined the evoked set of consumers interested in these cars. This set included twelve brands in the $8,500$ to $16,500$ price range. The first three columns of Table 1 provide a list of the twelve cars along with their late 1984 list prices and U.S. market shares. Total share of the twelve cars was $11.222\%$ of U.S. sales. The Olds and Ford brands have “twins” in the Buick and Mercury lines. We did not include these cars in the consumer survey but did use their market shares in the subsequent logit and optimal new brand analyses.

We elicited 19 differentiating attributes from these initial respondents using the repertory grid methodology (Kelly 1955). We then conducted 15 personal interviews in which we collected paired similarity data and ratings of each car on all 19 attributes. These data were used in individualized NMDS and aggregate Factor Analysis. For each consumer we used only those brands with which they were familiar. The two procedures were used to ensure convergent validity in the identification of the consumers’ underlying attribute space. We identified five attributes which describe this market: Performance, Dependability, Comfort, Prestige and Exterior Styling. While the attributes identified are specific to this set of cars they are quite consistent with those identified in other studies of the automobile market. Pekelman and Sen (1974) also identify dependability, comfort and styling in addition to acceleration, youthfulness and warranty. Acceleration is clearly

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Familiarity</td>
</tr>
<tr>
<td>Olds Ciera</td>
<td>9,712</td>
<td>2.350</td>
<td>4.0</td>
</tr>
<tr>
<td>Honda Accord</td>
<td>8,845</td>
<td>1.215</td>
<td>4.0</td>
</tr>
<tr>
<td>Volvo DL</td>
<td>12,940</td>
<td>0.438</td>
<td>4.0</td>
</tr>
<tr>
<td>Cadillac Cimarron</td>
<td>12,605</td>
<td>0.178</td>
<td>4.0</td>
</tr>
<tr>
<td>Olds Calais</td>
<td>8,499</td>
<td>0.119</td>
<td>4.0</td>
</tr>
<tr>
<td>Toyota Cressida</td>
<td>14,259</td>
<td>0.340</td>
<td>4.0</td>
</tr>
<tr>
<td>Ford Thunderbird</td>
<td>10,249</td>
<td>1.521</td>
<td>4.0</td>
</tr>
<tr>
<td>BMW 318i</td>
<td>16,430</td>
<td>0.283</td>
<td>4.0</td>
</tr>
<tr>
<td>Nissan Maxima</td>
<td>11,899</td>
<td>0.673</td>
<td>4.0</td>
</tr>
<tr>
<td>Chrysler LeBaron</td>
<td>9,099</td>
<td>0.974</td>
<td>4.0</td>
</tr>
<tr>
<td>Olds Cutlass Supreme</td>
<td>9,797</td>
<td>2.980</td>
<td>4.5</td>
</tr>
<tr>
<td>Audi 4000S</td>
<td>12,680</td>
<td>0.151</td>
<td>4.0</td>
</tr>
</tbody>
</table>

* The attribute levels specified are the modes of perceptions for each car by all consumers except those who had just purchased the car or had not heard of it (i.e., gave the car a familiarity rating of 1). We thus attempted to avoid both positively and negatively biased perceptions. We assume that these modes closely approximate the true attribute levels of each brand. Noninteger values occur due to ties or near ties for the mode.
Table 2
Average Goodness of Fit Measures

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model</th>
<th>Proportion of Correctly Estimated Paired Comparisons</th>
<th>Proportion of Correctly Estimated First Preferences</th>
<th>Spearman’s Rank Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>UVEC</td>
<td>0.9263</td>
<td>0.841</td>
<td>0.9022</td>
</tr>
<tr>
<td></td>
<td>ULOG</td>
<td>0.9272</td>
<td>0.852</td>
<td>0.9073</td>
</tr>
<tr>
<td></td>
<td>USQR</td>
<td>0.9258</td>
<td>0.837</td>
<td>0.9071</td>
</tr>
<tr>
<td>Certainty</td>
<td>CVEC</td>
<td>0.9125</td>
<td>0.767</td>
<td>0.8846</td>
</tr>
<tr>
<td></td>
<td>CLOG</td>
<td>0.9119</td>
<td>0.777</td>
<td>0.8852</td>
</tr>
<tr>
<td></td>
<td>CSQR</td>
<td>0.9120</td>
<td>0.763</td>
<td>0.8885</td>
</tr>
</tbody>
</table>

*A A specification of the models is provided in Appendix A.

connected to performance. Agarwal and Ratchford (1980) use objective characteristics which were found to correlate highly with a set of independent perceptual dimensions. The characteristics they use are engine displacement, passing time, handling, ride, luggage volume and rear leg room. These seem to be related to our performance and comfort attributes. Agarwal and Ratchford also note that they could not find an objective characteristic to measure styling which they had found to be an important perceptual dimension.

We then purchased from Polk in January 1985 a listing of a nationwide sample of 1100 November 1984 new car registrations. These registrations related only to the 12 cars in our evoked set. We mailed these new car buyers a questionnaire in February 1985 which elicited their attribute ratings of all 12 cars on a scale ranging from 1 (very low) to 7 (very high). A seven-point scale also was used for their familiarity with the cars, although here each point rather than just the ends of the scale was specified. The last six columns of Table 1 provide the modal ratings of the 12 cars. In addition, a preference ranking of the cars given a specified list price was obtained. The consumer’s income, price actually paid, and dollar value of optional extras ordered also were elicited. The response rate was 31%. The number of useable questionnaires was 283, which accounts for 26% of the total sample. The demographic profile of the respondents matched the profile of buyers of these type cars provided to us by General Motors.

Estimation of the individual multi-attribute expected utility models defined in Appendix A was done using LINMAP (Srinivasan and Shocker 1973). Several empirical studies have found that LINMAP compares favorably with other estimation techniques with respect to both stability of the parameter estimates and predictive ability (Pekelman and Sen 1974; Jain et al. 1979; Cattin and Wittink 1982; Horsky and Rao 1984). In the estimation, the familiarity measure is used to approximate the variance of the overall value, \( \eta^2 \). This variance is assumed to equal \( \eta(7 - \text{familiarity rating})^4 \), where \( \eta \) and \( \delta \) are to be determined through estimation. The usual payment period in 1984 was four years and the interest rate was 13.71%. Consequently, the yearly payments are \( \nu R = [0.1371/(1 - (1.1371)^{-4})]R = 0.3412R \). Table 2 provides the average values of the proportion of correctly estimated paired comparisons, the proportion of correctly estimated stated first preferences and Spearman’s rank correlation coefficient for each model.

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\(^2\) Specifically we stated "... The car you are most likely to buy (at the given sticker price) should be ranked 1 and the least likely 12..."

\(^3\) In other words we assume that less uncertainty is associated with the more familiar cars. It should be noted, however, that a high familiarity rating does not necessarily imply a high preference ranking. The familiarity scale was defined to measure past personal experience with each brand whether it be positive or negative.
### Table 3

**Estimated Attribute Weights**

<table>
<thead>
<tr>
<th>Variable</th>
<th>LINMAP Results</th>
<th>Updating Results</th>
<th>Average Updated Weight&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Estimated Weight</td>
<td>Predicted Utility Multiplier</td>
<td>Updating Coefficient</td>
</tr>
<tr>
<td></td>
<td>$\bar{w}_j$</td>
<td>$\alpha$</td>
<td>$\beta_j$</td>
</tr>
<tr>
<td>Performance</td>
<td>0.115</td>
<td>3.87</td>
<td>1.25</td>
</tr>
<tr>
<td>(14.4)&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(6.7)</td>
<td>(3.4)</td>
<td>(5.5)</td>
</tr>
<tr>
<td>Dependability</td>
<td>0.176</td>
<td>3.87</td>
<td>0.06</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(3.4)</td>
<td>(5.5)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Comfort</td>
<td>0.110</td>
<td>3.87</td>
<td>0.06</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(5.5)</td>
<td>(3.6)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Prestige</td>
<td>0.130</td>
<td>3.87</td>
<td>-0.55</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(5.5)</td>
<td>(3.6)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Style</td>
<td>0.166</td>
<td>3.87</td>
<td>0.06</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(1.4)</td>
<td>(1.4)</td>
<td>(1.4)</td>
</tr>
<tr>
<td>Remaining Budget</td>
<td>0.127</td>
<td>3.87</td>
<td>1.01</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(7.9)</td>
<td>(7.9)</td>
<td>(7.9)</td>
</tr>
<tr>
<td>Uncertainty</td>
<td>0.176</td>
<td>3.87</td>
<td>—</td>
</tr>
<tr>
<td>(14.4)</td>
<td>(1.4)</td>
<td>(1.4)</td>
<td>(1.4)</td>
</tr>
</tbody>
</table>

<sup>a</sup> The average updated weights are computed so as their absolute values sum to one. That is,

$$\bar{w}_j^* = \frac{|\alpha \bar{w}_j + \beta_j|}{\sum_{j=1}^f |\alpha \bar{w}_j + \beta_j|}.$$  

The average estimated weights (LINMAP results) also sum to one.

<sup>b</sup> Values in parentheses are t-values.

Specified in Appendix A. A search over a range of values for $\eta$ and $\delta$ found fit to be best when $\eta = 1$ and $\delta = 0.5$. Where applicable the reported results use these values. Based on the results presented in Table 2, it seems that models incorporating uncertainty outperform those which do not. Of the models which incorporate uncertainty the functional form which seems to be best is the ULOG model.<sup>4</sup> This model provides the best fit and has the appealing characteristic that the utility for incremental units of the attributes and all other goods is decreasing. Thus, for the rest of the paper the functional form used for the multi-attribute expected utility function is

$$E[U(z, Y - \nu R)] = \sum_{j=1}^f w_j \ln z_j + w_{j+1} \ln (Y - \nu R) - \frac{1}{2} r s^2. \quad (8)$$

In the process of evaluating the models, the attribute weights specified in model (8) were estimated on an individual basis.<sup>5</sup> The average attribute weights for the ULOG model across our sample of 283 consumers are provided in the first column of Table 3. The values indicate that, on average, dependability and style have the most impact in forming consumers’ stated preference ranks. The next most important attribute is prestige which is followed by the remaining budget and performance. Comfort is the least important attribute. Surprisingly, the two variables one would expect to be very important are estimated, on average, to be relatively unimportant. Remaining budget certainly should have a major impact on the consumer and performance should be a key concern.

<sup>4</sup> Strictly speaking the log and square root models (as well as the logit model used later) require the attribute ratings to be ratio scaled. Interval-scaled perceptions, however, are commonly used and hopefully are robust.

<sup>5</sup> LINMAP estimation was conducted on the standardized $f(z_j)$ and $f(Y - \nu R)$ values, where $f(\cdot)$ is the linear, natural log or square root function. $s^2$ also is standardized.
to sporty sedan buyers. Another interesting finding reported in Table 3 is the importance of accounting for consumer uncertainty.

The probability that brand \( m \) will be chosen by consumer \( n \) can be specified using equations (5), (7) and (8) as:

\[
P_n(m) = \frac{\exp \left\{ \alpha \sum_{j=1}^{\lambda_i} \tilde{w}_{jn} \ln z_{jm} - \frac{1}{2} \hat{r}_n s_{nn} \right\} \sum_{k=1}^{M} \exp \left\{ \alpha \sum_{j=1}^{\lambda_k} \tilde{w}_{kn} \ln z_{jk} - \frac{1}{2} \hat{r}_n s_{kn} \right\}}{\sum_{k=1}^{M} \left\{ \exp \left\{ \alpha \sum_{j=1}^{\lambda_k} \tilde{w}_{kn} \ln z_{jk} - \frac{1}{2} \hat{r}_n s_{kn} \right\} \right\}}.
\]

In the estimation of equation (9), the price of the chosen car was taken as the price actually paid by consumer \( n \) minus the price of all nonstandard options he ordered and paid for. As the prices of the cars not chosen we took the average of the options adjusted prices paid for the specific car by those consumers who did buy it.\(^6\) All other attribute levels were the individually perceived ones used earlier. A weighted maximum likelihood estimation procedure was used for the estimation of \( \alpha \) and the \( \beta_j \)'s. These parameters are homogeneous across the population. The weighting is necessary because our choice-based sample was not exactly proportional to the prevailing market shares. Furthermore, the market shares of the Ford and Oldsmobile brands were enhanced by the shares of their corporate twins. The homogeneity of the updating coefficients is necessary because only one choice observation per individual is available. Looked at from a different perspective the above updating procedure provides a way of incorporating individual level differences in brand perceptions and attribute weights into a cross-sectional logit estimation.

In the estimation we included two cars in addition to the 12 cars discussed earlier. Hence, \( M = 14 \). The reason for the addition of these two cars is that the logit model (due to the nature of equation (9)) leads to a nonzero probability of choice for any car specified. In addition to the cars we considered there are a large number of less expensive cars and a smaller number of more expensive cars which were available to our consumers. However, none of our consumers chose to buy these cars and this information must somehow be brought to the “attention” of the logit estimation procedure. If \( M = 12 \), no information concerning preferences for cars outside the elicited set is used in the logit estimation, even though this information might be relevant to the consumer and of interest to the firm. Since we did not realize this problem at the data collection stage and did not elicit from our sample attribute perceptions and preference rankings for an inexpensive and an expensive car, we constructed two hypothetical cars based on the considered cars specified in Table 1. One hypothetical brand has a price of $7,000 and attribute levels of 3 or 4 for each attribute and the other has a price of $18,000 and attribute levels of 6 or 7. The familiarity of both was taken to be 4 which is the mode of the consumers’ familiarity with the cars in the evoked set. With this specification our hypothetical inexpensive car is inferior on the attributes to the Oldsmobile Calais and is also $1,500 lower in price. Our hypothetical expensive car is superior on the attributes to the BMW 318i and $1,500 more expensive.\(^7\)

The estimated updating coefficients specified in equation (9) are presented in the middle two columns of Table 3. The resulting average updated weights are given in the last column of Table 3. The order of attribute importance, on average, has now changed considerably to performance, price (remaining budget), dependability, style, comfort and prestige. The fourth and fifth largest originally weighted attributes, performance and

\(^6\) This is an imperfect assumption since a consumer who bargained hard for the car he purchased is assumed to only do “average” bargaining on other cars. The sampling design presented later in the improvements section of the paper measures bargaining on all cars considered.

\(^7\) It should be noted that the IIA property implies that given a utility function with known parameters, the relative choice probabilities remain the same regardless of the consideration set. This does not mean that the estimation of the utility function is independent of the sample used or the amount of variability in attribute levels represented in that sample.
price, have now become the first and second most important and by a wide margin. Prestige moves from being the third most important attribute to being the least important. In fact, since these weights are averages there is a sizable portion of the population for whom the weight of prestige becomes negative. This most likely implies that when faced with an actual choice some consumers shy away from the prestigious high priced cars which they state to be preferred. Alternatively, they opt for the more tangible attribute performance and consider seriously the amount left over for other goods. In general, the average updated weights appear to be more consistent with our expectations. In particular, performance and remaining budget are found to be of key importance to sporty sedan buyers. The results are also consistent with the hypothesis that, on average, the importance of the remaining budget is higher at the point of purchase than is reflected in stated preferences.

The updating results change little if the attribute compositions or prices of the two added brands are changed slightly. If the estimation is done using only the original 12 brands, the updating results point in the same direction but are less pronounced. For example, the updating of the remaining budget component is 75% of the magnitude reported in Table 3. It should be noted that the magnitudes of the estimated updating coefficients are probably biased downwards. We elicited data from consumers who a few months earlier had bought a car and, therefore, it is likely that some post-purchase updating has been incorporated in their attribute and preference statements.

Expected Aggregate Demand

If individuals' choice probabilities are independent and the sample is representative of the target population, the central limit theorem can be used to calculate the joint probability distribution of market shares. This means that the expected market share of brand \( m \) is

\[
E(MS_m) = \frac{\sum_{n=1}^{N} P_n(m)}{N}.
\]

where \( N \) is the sample size. However, in our case we have a nonproportional choice-based sample. As a result the sample individuals were weighted by \( \phi_n \) to correct for the actual market shares of the chosen cars based on a procedure proposed by Manski and Lerman (1977). Expected market share then becomes

\[
E(MS_m) = \sum_{n=1}^{N} \frac{\phi_n P_n(m)}{N},
\]

where \( \phi_n \) is the population share (i.e., observed market share including twins) of the brand chosen by individual \( n \) divided by its sample share. Equations (9) and (11) provide the expected market share of all existing brands. Expected brand sales equal the product of expected market share and total industry sales. If a new brand were to be introduced into the market, its probability of purchase by a consumer based on its attributes and price could be computed using equation (9) with \( M + 1 \) rather than \( M \) brands. Its market share and sales then can be forecasted based on equation (11).

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8 Interestingly, if we use price rather than income minus price in the analysis the updating of prestige becomes positive. This may indicate that high income people choose prestigious cars and if income effects are omitted prestige picks up its impact. Another finding is that goodness of fit is far superior when AOG rather than price is included as a variable in the utility function.

9 An improved longitudinal sampling technique which avoids this problem is suggested later in the paper.
The Firm's Multi-Attribute Cost Function

To determine the most profitable entry position and price given competitive reaction, the entrant must estimate not only the demand functions but also the cost functions faced by itself and its competitors. One possibility is that the entrant knows the cost of a potential new brand based on the levels of its attributes and the quantity produced. However, we assume that the entrant lacks such knowledge due to inexperience or complexity and, therefore, wishes to recover the cost function from market data such as the sales of existing brands, their prices, etc.

Cost function estimation using market data in market situations other than oligopoly has been previously investigated. Estimation of the cost function facing a monopolist was performed by Rohlfs (1974) and Rosse (1970). Both estimate how costs relate to quantity produced and recognize that profit maximizing behavior implies marginal revenue with respect to quantity (MR) equals marginal cost with respect to quantity (MC). They simultaneously evaluate two equations, one corresponding to the demand function and the other relating to MR = MC. The variable cost function follows from the marginal cost function.

Estimation of market demand and supply curves in a perfectly competitive homogeneous goods market is commonly used to illustrate the simultaneous equations estimation technique (see Working 1927). In a perfectly competitive heterogeneous goods market a two-stage estimation framework has been proposed by Rosen (1974). Price, consumer level demand and variable costs are defined with respect to the attribute levels and do not depend on quantity. In the first stage of the estimation the hedonic price function, \( p(z) \), which maps the available price and attribute bundle pairs is estimated. A continuum of brands, depicted by \( p(z) \), is assumed to exist, and "competition prevails because single agents\(^{10}\) add no weight to the market and treat price as parametric to their decisions" (Rosen, 1974, p. 35). This means that the marginal prices and the levels of each attribute depend on the simultaneous actions of the individual and the firm. Thus, the continuous hedonic price function is the differentiated products analog to the single market clearing price which occurs in a perfectly competitive homogeneous goods market. Consequently, in the second stage the estimated hedonic price function is used as input into the simultaneous estimation of individual level demand and firm unit marginal costs defined with respect to each attribute (Agarwal and Ratchford 1980; Witte, Sumka and Erekson 1979).\(^{11}\)

In our oligopolistic market, variable costs as a function of the attribute levels will be estimated using market data concerning the existing brands. Before entry, the existing brands are assumed to be in a price equilibrium. Firms are able to react instantaneously with price changes to any alteration in market conditions. Other changes such as in attribute space location are very costly and as a result are enacted only when considerable shift in consumer tastes or in competitive offerings occurs. Moreover, these types of changes may take years to implement and only slowly penetrate consumers' perceptions. Robinson (1988) provides evidence that in the short run firms in a multitude of industries rarely react to entry by repositioning and if they do react they generally alter price.

For simplicity, we assume that each brand behaves as if it is an independent firm. The profit function for each brand is

\[
\Pi_m = [p_m - c(z_m)]S_m(Z, p) - FC_m, \quad m = 1, \ldots, M, \tag{12}
\]

where \( S_m(Z, p) \) are the sales of brand \( m \) which depend on the prices of all brands, \( p \), and on the attribute locations of all brands, denoted by the matrix \( Z \). \( FC_m \) are the fixed costs.

\(^{10}\) That is, firms and individuals.

costs of the brand and \( c(z_m) \) is the average variable unit cost which is depicted as a function of the attribute levels. White (1971) cites evidence of scale economies. However, in our subsequent empirical analysis we did not find that variable costs depended on output, \( S_m(Z, p) \). Consequently, variable unit costs are not modeled as depending on quantity. This also simplifies the analysis since variable unit costs then equal marginal costs. Subsequent empirical analysis incorporating dummy variables for European and Japanese manufacturers also did not show the existence of different cost structures. Due to these findings and data limitations, \( c(z_m) \) is assumed to be the same for all brands.\footnote{Evidence that supports this assumption for the automobile industry is found in Fuss and Waverman (1986).}

The joint maximization of the \( M \) profit functions with respect to own price leads to the price equilibrium. This is equivalent to the simultaneous solution of the \( M \) first order conditions,

\[
\frac{\partial \Pi_m}{\partial p_m} = \left[ p_m - c(z_m) \right] \left[ \frac{\partial S_m(Z, p)}{\partial p_m} \right] + S_m(Z, p) = 0.
\] (13)

This can be reformulated as

\[
p_m + \left\{ \frac{S_m(Z, p)}{\frac{\partial S_m(Z, p)}{\partial p_m}} \right\} = p_m \left( 1 + \frac{1}{e_m} \right) = c(z_m),
\] (14)

where \( e_m = [\partial S_m(Z, p)/\partial p_m]/[S_m(Z, p)/p_m] \) is the elasticity of demand with respect to own price for brand \( m \). Equation (14) implies that MR = MC for each brand. The price of the brand in this oligopolistic environment exceeds the price which would have been charged for the brand in a perfectly competitive market (in which \( e_m = -\infty \) and, hence, price equals marginal cost). However, the equilibrium price is not as high as the price that would have been charged by a monopolist since the monopolist’s sales are not impacted by the prices and attribute positionings of competitive brands.

A multiplicative average variable unit cost function,

\[
c(z_m) = \prod_{j=1}^{J} z_{jm}^\gamma_j,
\] (15)

is assumed which allows the incremental cost of each attribute to be increasing, \( \gamma_j > 1 \), or decreasing, \( 0 < \gamma_j < 1 \), as the attribute level is increased.\footnote{Alternative functional forms also were investigated. These functional forms did not outperform the multiplicative model in terms of fit. The model also has the appealing features of cost interactions and nonlinear incremental attribute costs.} Thus, we have for each brand its demand as a function of its attribute levels and price as specified in equations (9) and (11) and its cost function as specified by a combination of equations (14) and (15) as well as equations (9) and (11). With the assumption that a price equilibrium currently exists in the market, these equations allow us to estimate the values of the \( \gamma_j \)'s. That is, the cost parameters \( \gamma_j \) in the following equation can be estimated:

\[
p_m + \left\{ \frac{S_m(Z, p)}{\frac{\partial S_m(Z, p)}{\partial p_m}} \right\} = c(z_m) = \prod_{j=1}^{J} z_{jm}^\gamma_j.
\] (16)

Our oligopolistic situation differs in a number of ways from the market structures for which the estimation procedures discussed earlier are used. It differs from the monopolistic
and perfectly competitive homogeneous goods cases in that: (i) Individual consumer level demand is modeled. Individual level demand is then summed to get aggregate demand facing each firm; (ii) The marginal cost function refers to a single firm not the industry (in a monopoly the firm is the industry); (iii) The multi-attribute model is used. Our situation differs from the Rosen perfectly competitive heterogeneous goods framework in that: (i) Each firm exerts oligopolistic power by choosing price; (ii) The firms’ decisions (prices) depend on quantity; (iii) Demand is defined with respect to each brand rather than each attribute; (iv) Marginal cost is defined with respect to quantity rather than a single attribute.

Due to the above differences, an alternative estimation procedure is proposed. In our situation individual consumers add little or no weight to the market but each firm wields some market power. Each individual consumer takes price roughly as given and has essentially no impact on the aggregate demand function facing each firm. Consequently, the aggregate demand function facing each firm can be taken as given. The firms choose price, and, hence, quantity sold, based on the demand and cost functions they face. A simultaneous estimation framework should provide little, if any, benefit relative to direct estimation. Basically, the individual level errors in equation (9) are likely to be uncorrelated or only slightly correlated with the firm level errors in equation (16). As a result, estimated parameters from the nonsimultaneous estimation of the two equations contain little or no bias.

Because the first-order conditions above relate to the derivatives of the profit function with respect to price, fixed costs drop out of the analysis. However, when a firm makes the decision whether or not to enter a market fixed costs play a role, and, hence, they need to be determined. There are two types of fixed costs which must be considered. The first relates to product, plant and equipment and research and development which are essentially start-up costs. The second corresponds to overhead costs which are unrelated to output or attribute space location. A new entrant must consider both types of costs when making an entry decision, while an existing firm in determining whether to remain in the market is concerned only with the overhead costs since start-up costs are sunk.

**Estimation of Costs**

The average variable unit cost function specified in equation (16) was estimated using demand $S_{m}(Z, p)$ and demand sensitivity to price $(\partial S_{m}(Z, p)/\partial p_m)$ estimates based on equations (9) and (11), observed market prices ($p_m$) which are assumed to be the profit maximizing equilibrium prices, and brand attribute levels ($z_{m}$) as inputs. In the automobile industry, in particular, it stands to reason that a price equilibrium exists. Manufacturers can react to changes in market conditions by offering rebates but cannot for a long while change the physical attributes of their brands. Each of the 12 brands is treated as an observation in equation (16). That is, $S_{m}(Z, p)$, $\partial S_{m}(Z, p)/\partial p_m$ and $p_m$ are all known values and combine to provide the values of the dependent variable $c(z_{m})$, while the independent variables are the $z_{pm}$. The unknown parameters $\gamma_i$ then are estimated using nonlinear regression. The cost function includes only four of the original attributes, performance, comfort, exterior styling and dependability, as we felt that prestige is not strongly tied to physical attributes the firm can alter. The estimation was performed, due to the reasons provided above, separately from the estimation of the demand side and, in fact, the demand estimates obtained in the previous section were used as inputs. In the demand analysis each consumer had a different perception of each brand’s attribute.

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14 Evidence that market power in the automobile industry exists is witnessed by studies that claim automobile manufacturers charge prices in excess of marginal costs (Bresnahan 1981; Hall 1986; Winston and Assoc. 1987) or earn abnormal profits (Kwoka 1984; White 1971, 1982).
levels. However, in order to estimate $c(z_{im})$ in equation (16) unique levels for the $z_{im}$ (the independent variables of the equation) are required. We used for each attribute of each brand the modes reported in Table 1.

Table 4 provides the cost function coefficients estimated through a nonlinear least squares estimation procedure.\textsuperscript{15} The fit is high and the standard errors are relatively large. This is partially due to the small number of degrees of freedom (eight). As hypothesized by Rosen (1974), all coefficients are greater than one. This implies that average variable unit cost is positively and increasingly related to the attribute levels. That is, incremental attribute improvements are increasingly costly. The estimated coefficients have some intuitive appeal. These results imply that increases in the size of a car and changes in its interior design and components (which would improve comfort) are on the margin the most expensive to perform. Next most expensive are external styling improvements such as a more streamlined body and mechanical improvements such as installation of higher quality moving parts and improved quality control (which would improve dependability). Finally, improvements related to acceleration and handling ability such as a stronger engine or enhanced suspension system would have relatively the least impact on variable costs.

Fixed costs, both start-up and overhead, for automobile brands need to be estimated too. Published figures pertaining to start-up costs in the automobile industry vary widely. Key factors behind this variation are the originality of the car design, size of the plant, and whether a new plant is built or an existing plant refurbished. When a relatively small new plant is built and virtually no R&D expenses are incurred, the entrant's start-up costs may be as low as $500 million (Ward's Auto World February 1984). As the originality of the design or plant size increases, start-up costs increase and may reach as high as $3 billion (Ward's Auto World February 1985). White (1982) estimates that an entrant's start-up costs for a 500,000 unit capacity plant would be on the order of $1.5 billion.

Total annual overhead costs are more difficult to estimate. Selling, administrative, and general expenses are commonly reported. However, a fraction of the cost of goods sold (COGS) also is unrelated to the amount of production. Consequently, an assumption is needed about what proportion of these costs is variable. Based on GM's 1984 Report to Shareholders, automobile revenues in 1984 were $80,499.3 million while sales were 8,256,000 units. This corresponds to an average revenue (wholesale price) of $9750. Selling, administrative, and general expenses comprise 4.8% of total revenue or $468 per unit while COGS represent 83.7% of revenues or $8,161 per unit. Assuming, say 10% of COGS are overhead costs ($816 per unit), a rough estimate of manufacturer overhead costs would be $468 + $816 = $1,284 per unit. Overhead costs for a plant with a 300,000 unit capacity then would be roughly $385.2 million.

\textsuperscript{15} Improvements on this method of estimating variable costs are discussed later in the improvements section of the paper.
Expected Costs for an Entrant

Earlier based on equation (11) we specified the demand an entrant can expect given its chosen location and price. Consistent with our past findings and assumptions, we now assume that the variable and fixed costs faced by the entrant can be approximated by the costs currently incurred by the existing brands. That is, the entrant’s variable costs as a function of its chosen attribute levels are defined by equation (16) and the parameter values reported in Table 4. Fixed costs, consisting of both start-up and overhead costs, are defined and approximated as above.

Attribute Location and Price for a New Brand

The most profitable attribute space location and price for a new brand is sought, given the locations of the existing brands and the understanding that these brands will change their prices in response to entry. The situation involves the simultaneous maximization of each existing firm’s profit function with respect to price and the entrant’s profit function with respect to price and location. In essence we are assuming that after entry (just as prior to it—see the cost estimation discussion) the market will be in a price equilibrium but not necessarily in a location equilibrium. Opportunities for entry may arise because of changes in consumers’ tastes (i.e., attribute weights) and incomes, technology, government regulations and economic conditions (e.g., the price of oil). If the existing firms react to these changes by changing their prices but do not change their locations or change them very slowly, opportunities for an entrant may present themselves. It should be noted that due to embedded perceptions the existing firms may not be able even in the longer run to drastically reposition their existing brands and may need to replace them with new brands. This may cause their reaction to market changes to be even slower.16

Entry in the Face of Competitive Price Reactions

The entrant’s choice of price and location allowing for competitive price reactions can be modeled as either a simultaneous or a two-stage game. The simultaneous game assumes that the entrant chooses price and location at the same time as the existing firms choose price. The two-stage game assumes that the entrant first chooses a location and then the entrant and existing firms simultaneously choose prices. Hauser (1988) and Moorthy (1988) use a two-stage game in their studies of equilibrium in oligopolistic markets. There is evidence to suggest that the development of a new brand (particularly in the automobile industry) may take several years. Consequently, the firm must make design decisions well in advance of a price decision. Thus, the two-stage game appears more appropriate and is used in our analysis.

The two-stage game involves the analysis of a price subgame for every possible location for the entrant. The entrant chooses a location and afterwards the existing firms and the entrant choose price simultaneously. A subgame perfect Nash equilibrium is sought. This means that, for every possible new location, the entrant solves for its profit maximizing price while assuming that its competitors will also alter their prices. For each possible new location this corresponds to the simultaneous solution of the \( M + 1 \) first-order conditions relating to the maximization by each firm of profit as specified in equation (12) with respect to own price,

\[
\frac{\partial \Pi_m}{\partial p_m} = S_m(Z,Z) + \{p_m - c(z_m)\} \left[ \frac{\partial S_m(Z, p)}{\partial p_m} \right] = 0, \quad m = 1, 2, \ldots, M + 1. \quad (17)
\]

16 Some cursory evidence of the difficulty in drastic repositioning of existing brands in the automobile market is the fact that in order to have entries in the luxury car market U.S. firms have acquired existing foreign brands (GM purchased the Saab line, while Ford purchased the Jaguar line) and Japanese manufacturers have introduced new lines and dealer networks under different names (Acura, Infiniti and Lexus).
The entrant then chooses the location and corresponding price which result in the most profit.\textsuperscript{17}

To Enter or Not to Enter

Once the entrant’s profit maximizing price and location are identified, profit is obtained by inserting these values into the profit function. This provides an estimate of profit for a single period (a year). However, a product such as a car has a product life which exceeds one year. Assuming market conditions do not change over the life of the brand, $T$, its net present value equals

$$
\sum_{t=0}^{T} \left\{ (1 + \sigma)^{-t} \left[ \text{Total Contribution - Overhead Costs} \right] \right\} - \text{Start-Up Costs}.
$$

$s$ is the discount rate. If this net present value is positive, the new brand concept should be retained for further product development and market testing. If the concept makes it through these additional stages, the brand should be introduced.

The New Car

An algorithm is used to identify the entrant’s profit maximizing price and attribute space location when existing brands respond to the entry through price changes. For each possible attribute bundle the following iterative procedure is used. First, solve for the best price of the entrant assuming no competitive reaction (existing prices are maintained). Then solve for the profit maximizing price of firm 1, given the entrant’s price and location and those for firms 2 through $M$ as well. Similarly, solve for firms 2 through $M$ each time incorporating any price changes made in earlier iterations. Then, start over beginning with the entrant, followed by firm 1, then firm 2, and so on. This cycling through the entrant and the twelve original firms continues until generated prices converge. The generated prices represent the Nash subgame price equilibrium pertaining to the entrant’s given attribute levels. A search over all possible attribute bundles is conducted and the one corresponding to the highest profit is chosen.\textsuperscript{18}

We searched for the market equilibrium a number of years after entry. Therefore, the prestige and familiarity of the new brand are assumed to be at a level of 4 which is the mode for the existing brands. The new brand’s recommended location, price, sales and profit are given in Table 5. The new brand will have a market share of 2.60% which is the second largest market share in this set of cars and will have the third highest profit.

The profits of all incumbents will decrease after entry. Interestingly, the new prices for six of the incumbents will be lower than in the pre-entry period while the other six will be higher. The good performance by the entrant results from the fact that the entrant has the freedom to choose both its price and location while the original firms can only alter their price.

The recommended location and price for the entrant is intuitively sensible. To be profitable the entrant must offer something different from what is offered by the existing firms. The entrant must either be differentiated perceptually (i.e., have a differentiated

\textsuperscript{17} If the game was a simultaneous one then the equations specified in (17) and the first-order conditions relating to the entrant’s optimal location on the $J$ attributes,

$$
\frac{\partial \Pi_m}{\partial x_m} = \left\{ p_m - c(z_m) \right\} \left[ \frac{\partial S_m(Z, p)}{\partial x_m} \right] - \left\{ \frac{\partial c(z_m)}{\partial x_m} S_m(Z, p) \right\} = 0, \quad j = 1, 2, \ldots, J,
$$

would need to be solved simultaneously.

\textsuperscript{18} We assume feasibility considerations restrict the possible attribute levels for the new brand to be 3, 4, 5, 6 or 7. In effect, we solve for the optimal prices at each of the 625 possible entrant locations. Additional constraints on the entrant’s possible position could be incorporated analogously.
attribute space location) or offer a brand similar to the ones currently offered but at a lower price. Based on Table 1 the existing brands have perceived attribute levels ranging mainly from four to six, an entrant with similar attribute levels must charge a relatively lower price in order to be purchased. The low price, however, results in low profit. Since attribute levels of three and seven differentiate the entrant perceptually, the entrant has localized market power and less pressure exists to charge a low price. Correspondingly, the entrant’s price of $10,197 is just below the median price after entry. The location of the new car indicates that the entrant has found that a place in the market exists for a car which is mechanically first rate but compromises on its style and comfort. Interestingly, the two attributes the entrant has decided to excel on, performance and dependability, are on average the most important attributes (see Table 3) and the least costly to manipulate (see Table 4).

Single-year total contribution (profits excluding overhead), overhead and start-up costs can be combined into a net present value (NPV) analysis. At first, after introduction, lack of awareness about the new brand will cause its familiarity and prestige ratings to be lower than at steady-state. Hence, its entry market share and profits will be lower. Nevertheless, for any reasonable discount rate and car life span, the new brand has a positive NPV. It should be noted, however, that the analysis pertains to total channel profits which are divided between the manufacturer and retailers.

From Perceptual Concept to Physical Brand

We have identified a new brand concept in terms of its price and perceptual attribute space location. However, this concept must be translated from the consumers’ perceptual space to the producers’ physical attribute space. Furthermore, the physical attribute space encompasses hundreds of engineering attributes. While we did not attempt this stage in our field study, we will outline a potential methodology to carry out this mapping.

Several studies (e.g., Hauser and Simmie 1981; Neslin 1981; Hauser and Clausing 1988; Narasimhan and Sen 1989) have shown that the consumers’ perceptual space is rooted in physical and engineering attributes. Narasimhan and Sen (1989) suggest that a perceptual attribute such as copy quality in copiers is based on physical attributes such as line width, darkness, gloss, spots, streaks, etc. These physical attributes in turn result from internal machine features—engineering attributes (lens and toner type, etc.). The connection between the physical and engineering attributes is said to be known to the design engineers, so Narasimhan and Sen examine the connection between the perceptual and physical attributes. They demonstrate through regression analysis that perceived copy quality can be linked to objective physical attributes. Similarly, Neslin (1981) finds a strong relationship between perceptual and physical attributes using ANOVA. Hauser and Clausing (1988) present a “house of quality” concept. They note that perceptual,
physical and engineering attributes can be related to one another through consumer surveys, engineering experience and experimental and statistical study results.

Following the above methodology we assume a similar connection can be established in cars. That is, we can estimate a function connecting, for example, the perceived comfort rating of a car with the physical attributes front and rear leg room, width and height of the car, luggage space, placement of engine, etc. This set of functions, one for each perceptual dimension, will be given to the design engineers. Along with these mappings they will be given the desired perceptual space location of the new brand and the target cost of production for that brand. This cost will be computed based on the cost function estimated earlier in equation (16). The assumption made is that since the existing brands which also are made up of physical (and engineering) attributes can be produced at their estimated costs, the predicted cost here is both feasible and efficient. The engineers will be requested to design a car which matches the perceived location and the planned costs. This task is far from being straightforward and will stretch the designers' creative abilities. The mapping from a perceptual attribute to physical and engineering attributes is clearly a one-to-many mapping. Moreover, as pointed out by Hauser and Clausing (1988) who discuss the automobile market, certain engineering attributes may affect more than one physical and perceptual attribute. Thus, it is quite possible that the designers will suggest several alternative new brands to fill the same perceptual location. These brands could then be used as the basis for prototypes which after further market testing and scrutiny may lead to a specific market introduction.  

Summary, Improvements and Future Research

In this study a methodology for the analysis of new brand positioning and pricing in an oligopolistic market was developed. Initially, estimates of individual level expected utility functions and brand demand and cost functions are made in terms of brand attributes and prices. Then, using a game theoretic approach, these results are used to derive the profit maximizing price and attribute space location of a new brand allowing for competitive price reactions. The methodology is illustrated using automobile market survey data. This methodology in conjunction with subsequent product development and market testing can help firms in their analysis of new brand opportunities.

The methodology outlined in this paper dealt with the positioning problem from its basic foundations of consumer utility functions and firm cost functions to the ultimate recommendation of a new brand. Along the way to the finish line shortcuts in the form of simplifying assumptions were made. These assumptions leave room for improvements in the proposed methodology and also suggest unaddressed issues which are left for future research.

Improvements

The methodology described in this paper can be improved in a number of ways. Key areas concern the data and procedures used to evaluate consumer demand and firm costs. Improvements in these areas require a study design of greatly increased complexity, cost and length. However, given the potentially large payoff a producer may receive from more accurate decision analysis, a real world study of this nature would be blessed with a much larger budget allowing improvement in the study design. Since these improvements concern measurement and estimation procedures, the discussion will remain in the context of the automobile market although their applicability is not limited to this product class.

To preclude potential consumer post-purchase updating of stated preferences and the

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19 For example, Urban, Hauser and Roberts (1988) provide a methodology for prelaunch forecasting for new automobiles.
brands' attribute perceptions (due to cognitive dissonance, purchase rationalization, etc.), attribute perceptions and preferences should be collected prior to purchase. However, since there is a considerable amount of consumer learning prior to purchase, the data should not be collected too much ahead of this time. A possibility is the following three-stage survey design. A brief preliminary telephone screening interview done on a very large random sample will ask individuals if they are in the market to replace their car (or buy their first car) and what is the set of cars they are considering. Provided that the respondent is in the market and that the cars he is interested in belong to the submarket of interest to the producer, the respondent will be mailed a questionnaire. The questionnaire will be accompanied by a small financial incentive and the identity of the respondent will be requested. The questions asked will concern the attribute perceptions and preference ranking of a set of cars which includes the cars in the generalized evoked set plus a few additional cars. A follow-up telephone interview will be conducted to ascertain if a car was purchased, what brand was selected, its price, the set of cars considered seriously at that final stage and the prices the consumer believes that he actually would have had to pay for those cars if purchased. These data would allow improved preference and choice analyses. The LINMAP preference analysis would be based on the pre-purchase attribute and preference data. The logit analysis of choice data would be based on just the consumer's stated evoked set and the prices he considered in his final evaluation. Consequently, this design also allows individual differences in bargaining power and evoked sets to be incorporated into the analysis.

One way of improving the cost estimation procedure would be to obtain from design engineers prior estimates of the relationship between the attributes and costs. These priors would then be “updated” based on the market equilibrium analysis. In those industries, such as the automobile market, where firms produce several brands it is possible if a large enough number of brands are evaluated for firm specific cost functions to be extracted, thereby relaxing the assumption of identical cost structures across firms. Such firm-specific cost functions may lead to profit functions which result in firm “specialization” in, for example, small or large cars.

Future Research

Further work remains to be done on the positioning and pricing problem. Future research topics relate to both measurement and optimization. A difficult measurement problem concerns the timeliness of the data available to estimate the demand and cost functions. From the time that the new brand positioning is determined until the brand actually appears in the marketplace a period of several years may elapse. During this time consumers' tastes may change. Some foresight with respect to these changes would be valuable. Similarly, identification of new attributes currently not manipulated by existing brands (such as no caffeine in soft drinks) could prove fruitful. A possible method to address these concerns may be through lead users (see, e.g., Urban and von Hippel 1988). Cost side changes also may occur. For example, new cost reducing technologies may evolve. Foresight with respect to such changes in the demand and cost functions will allow the manufacturer to generate more accurate expectations as to the actual market performance of its new brand.

The positioning optimization framework also could be made more realistic. Several extensions are possible. First is the issue of price dynamics. Familiarity ratings of a new brand are dynamic and will increase with time. They are quite likely to be dependent on the manufacturer's reputation, the number of years in the market, past market share or sales, publicity and advertising intensity. A new brand should be designed with the attribute levels which will be profit maximizing at the steady-state equilibrium but its price should vary as to maximize each period's profit (or total discounted profits if past sales play a role). A second issue is more sophisticated competition. The existing brands
may eventually change their locations and another brand may enter at a later date. The long-run position and price of the entrant could be determined assuming that the incumbents move to their profit maximizing locations (possibly with some constraints on how much repositioning is feasible given their existing perceptual locations) or that a second entrant will choose the best location and price available given the locations of the existing brands and the first entrant. Product line considerations are another area of interest. The new brand may be introduced by a firm which already has a brand in the market and, therefore, would be concerned about cannibalization. Alternatively, the entering firm may find it more profitable to introduce two brands rather than one. Such multi-brand entries also may block future competitive entries and subsequent profit erosion.20

20 This paper was received October 31, 1988 and has been with the authors 24 months for 2 revisions. This paper was processed by Richard Staelin.

Appendix A. Expected Utility Models

(I) Models Incorporating Uncertainty

Note: All other goods (Y - xR) is treated as an additional (J + 1th) attribute.

UVEC

Utility = \( U = -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j z_j \right) \right\}; \quad r > 0, \)

Expected Utility - E = \( -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j E[z_j] - \frac{r}{2} s^2 \right) \right\}. \)

equiv = \sum_{j=1}^{J+1} w_j E[z_j] - \frac{r}{2} s^2.

ULOG

\( U = -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j \ln z_j \right) \right\}; \quad r > 0, \)

\( E = -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j E[\ln z_j] - \frac{r}{2} s^2 \right) \right\}. \)

equiv = \sum_{j=1}^{J+1} w_j E[\ln z_j] - \frac{r}{2} s^2.

USQR

\( U = -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j \sqrt{z_j} \right) \right\}; \quad r > 0, \)

\( E = -\exp\left\{-r \left( \sum_{j=1}^{J+1} w_j E[\sqrt{z_j}] - \frac{r}{2} s^2 \right) \right\}. \)

equiv = \sum_{j=1}^{J+1} w_j E[\sqrt{z_j}] - \frac{r}{2} s^2.

These three models are generically expressed as \( U = a - b \exp \{-rV \} \) where \( V \) is the overall value. Without loss of generality, we set \( a = 0 \) and \( b = 1 \). \( U \) shows constant absolute risk aversion with respect to \( V \). The strength of the individual’s risk aversion is measured by \( r \).

(II) Models of Certainty

Models assuming certainty are of the same form as those specified in Part I of the Appendix except that the \( rs^2/2 \) term is not included. These models will bear the names of CVEC, CLOG, and CSQR.

References


General Motors Corporation (1984), Report to Shareholders.


