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CUSTOMER VALUE ANALYSIS IN A HETEROGENEOUS MARKET

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In recent years, customer value has become a major focus among strategy researchers and practitioners as an essential element of a firm's competitive strategy. Many firms have been interested in Customer Value Analysis (CVA) which involves a structural analysis of the antecedent factors of perceived value (i.e., perceived quality and perceived price) to assess their relative importance in the perceptions of their buyers. We develop a statistical approach for performing CVA utilizing a recursive simultaneous equation model that is formulated to accommodate buyer heterogeneity. In particular, the proposed finite-mixture methodology allows one to estimate the relative effects and integration rules of perceived value drivers at the market segment level, as well as to simultaneously determine the (unknown) segments themselves. We demonstrate the utility of the proposed methodology via an actual commercial application involving a large electric utility company. Finally, we discuss the contributions of our research from the perspective of firm strategy and how it may be extended in the future.

INTRODUCTION

Understanding what buyers value within a given offering, creating value for them, and then managing it over time have long been recognized as essential elements of every market-oriented firm's core business strategy (Drucker, 1985; Porter, 1985, 1998; Slater and Narver, 1998). Determining what the customer wants in a product or service also helps a firm formulate a clear statement of its "value proposition," i.e., the communication of the unique benefits and utility obtainable only from the focal product in contrast to those from its competitors. Porter (1985) notes that a firm's competitive advantage stems from its ability to create value for its buyers that exceeds the firm's cost of creating it. More recently, value has attracted an even greater interest in the strategy literature and among senior firm executives as the focus has shifted to the compelling issue of how customers can become "co-producers of value" and therefore how firms can "co-opt" their competencies (e.g., Prahalad and Ramaswamy, 2000; Ramirez, 1999). Authors have noted that value co-production between the firm and its consumers has now become more likely and achievable with rapidly-evolving technological innovations (e.g., the Internet) and increasing obfuscation of a firm's traditional boundaries.

A necessary antecedent to a firm's (e.g., web retailer) defining a value proposition or leveraging customers' competencies by engaging them in the co-production of value must be a thorough and comprehensive identification and analysis of *what it is that they (i.e., customers) actually value*. As Ramirez (1999:49) states, to study how value is co-produced by two or more actors must "invite us to rethink value creation itself." A major goal for

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firms, as they begin to design their value-delivery programs, is to conclusively assess how customers accord weights to the various benefits they receive versus the price they pay. Not surprisingly, more and more firms therefore have been performing such Customer Value Analysis as part of their overall customer value management (CVM) programs to articulate the "voice of the customer" in managerial decision-making. Interestingly, as we denote in this paper, CVA may be viewed as having evolved from Porter's (1985) seminal discussion of the role of buyer-perceived value in shaping firm strategy. A number of CVA models have been advanced that allow the structural analysis of the perceived drivers of customer value (typically quality and price). Anderson and Narus (1998:54) discuss how businesses stand to profit from the resulting inferences gleaned from customer value models, and Gale (1994) reports that firms such as Fedex, AT& T, and Xerox have been able to improve firm performance through enhancing customers' loyalties and reduce their churn rates.

One key aspect that is missing in many existing CVA approaches is that they *do not explicitly account for buyer heterogeneity and effectively assume that buyers are all affected by the antecedent factors in the same manner*. In contrast, a major finding from studying buyers' subjective "definitions" of value is that value perceptions are idiosyncratically developed vis-à-vis *both* the buyer and the product/service category (Zeithaml, 1988). In other words, corresponding to a particular product or service there are indeed heterogeneous interpretations of customer-perceived value, and multiple customer segments may assign differential importance weights to the value drivers (perceived quality and price). Clearly, an aggregate analysis (ignoring heterogeneity) can yield misleading estimates of these impacts, and provide an erroneous view of the market.

In this paper, we develop an improved CVA technique which accommodates buyer heterogeneity through a finite-mixture, simultaneous-equation modeling approach that permits the analysis of customer value antecedents and their differential weighting by buyer segments, which are simultaneously derived and not known à priori. Subsequently, we are able to profile the derived segments from individual descriptor variables. Our methodology also permits different functional forms of value to be specified and tested. The net utility of this approach is a better modeling tool that firms can apply to understand how their buyers integrate different factors to arrive at their value perceptions.

BACKGROUND

In the academic literature, value has been conceptualized in various ways. In most places, customer value has been defined as a tradeoff between (customer-perceived) quality and (customer-perceived) price. Perceived quality, in turn, has been conceptualized as buyers' "judgment about a product's overall excellence or superiority" (Zeithaml, 1988:3), and perceived price is defined as the consumers' subjective perception of the objective price of the product (Jacoby and Olson, 1977). Similarly, Porter (1985:131) likens buyer value as a tradeoff of buyer-perceived performance and buyer cost. A comparable view is taken in industry where perceived value has been variously defined in much of the popular press as "quality at the right price" or as "affordable quality".

From an empirical perspective, the thesis that perceived value is a function of perceived quality and perceived price has received broad support. For instance, Chang and Wildt (1994) find perceived value is positively related to quality, but negatively to price. Similarly, in investigating the dimensionality of perceived value from customer responses, Sinha and DeSarbo (1998) report the existence of two latent factors or dimensions: one, a quality (or benefits) dimension and the other a price-based dimension. Importantly, value has been found to be linearly related with both the factors, positively related to quality but negatively with price. (The price-quality interrelationship has been found to be weak.) In our model set-up (described below), we therefore specify value as a linear function of both of these variables, which are also treated to be exogenous. Next, we discuss in greater detail how customer value is pertinent to both strategy researchers and industry practitioners.

Customer value and strategy

From a firm's perspective, customer value analysis is relevant for two important reasons. First, a number of strategy researchers have highlighted the need to account for changing customer perceptions and expectations in devising firm strategy (e.g., Prahalad and Hamel, 1994; Slater and Narver, 1998). Specifically, Porter (1985), in discussing a firm's goal in using differentiation as a competitive advantage, has introduced the notion of a "buyer's value chain" (as contrasted from that of a firm). This value chain represents the factors and activities that are important from the point of view of buyers as they begin to derive value from the products and services they buy. Moreover, according to the author, the success of a firm's differentiation strategy depends on the extent to which the firm's value chain relates to the buyers' one. Importantly, the value chain for a buyer extends from their broad notions of performance and cost into more concrete and measurable characteristics (called "purchase criteria" by Porter) that firms can identify in their offerings. This idea is similar to a means-end chain (e.g., Zeithaml 1988) where buyer-perceived performance or quality is developed as a *second-order phenomenon* from their perceptions of "objective" (intrinsic and extrinsic) attributes of a firm's offering. The CVA methodology is well-suited to identify and calibrate the effects of the "lower-level" attributes on overall buyer-perceived value.

The second reason why customer value should be of interest to strategy researchers and practitioners is the positive economic consequences that it has for firms. There is now an increasing body of evidence that establishes that firms that deliver superior value secure loyal customers and, in turn, reap favorable firm-level outcomes in terms of higher revenues, lower churn, and less overhead costs (see Reichheld, 1996). At the individual buyer level, these studies have shown that value (mediated through loyalty) results in increased purchases, increased cross-buying, increased word-of-mouth referrals, and less returns. Likewise, in the strategy literature, Nayyar (1995) finds that changes in a firm's customer service level are positively associated with stock market reactions. Thus, customer service increases result in higher market valuation and vice versa. Although, Nayyar does not explicitly focus on customer value, clearly customer service is one of the value-creating activities that a firm may implement.

Modeling customer value

There are three salient aspects in modeling value: (1) incorporating its dependence on lower-level physical attributes; (2) the issue of functional form; and (3) buyer heterogeneity in the integration of perceived value drivers. As earlier stated, while customer-perceived value may be viewed as an integration of such "higher-level" factors as perceived quality and perceived price, perceived quality in turn has been shown to be formed from the lower-level, tangible attributes of a product or service. To this extent, both perceived value and quality may be considered a somewhat more complex, multidimensional, and abstract "B-attributes" (Olson and Reynold 1983). Therefore, in our modeling formulation, we assume perceived quality to be a weighted combination of the customer-perceived attribute performance/information.

An unresolved empirical question concerns the question of the *functional form* of perceived value (v): how the perceived value antecedents, i.e., quality (q) and price (p), are integrated in the minds of buyers. Monroe (1990) suggests a ratio or proportional specification, i.e., $\nu = \frac{q}{p}$, implying the perceived value is judged to be quality at unit price in buyers' minds. Other authors (e.g., Hagerty, 1978; Levin and Johnson, 1984) argue for a subtractive formation, i.e., $\nu = q - p$. The latter form implies a linear, compensatory rule in which people integrate price and quality in a subtractive manner, and that they subtract perceptions of higher price from those of higher quality. Between the two functional forms, the difference or subtractive rule seems to have received broader support. Our proposed modeling framework will permit the testing of alternative specifications of perceived value to explicitly address this issue.

Issue of heterogeneity

As noted before, a major omission in previous customer value models has been their authors' failure to incorporate heterogeneity in the integration of the underlying dimension of value. But, there are both substantive and methodological concerns associated with this aggregate analysis strategy. An aggregate analysis may inappropriately pool members from heterogeneous sub-populations resulting in parameter estimates that are inconsistent. Further, analysis by a-priori customer segments/groups (e.g., formed on the basis of firmographics) provides no assurance that an optimal segmentation is in place with respect to the CVM model of interest. Segments may be easy to understand and reach, but may not produce differentiated CVM models with the best possible explanatory power. That is to say, these a-priori segments may be firmographically different but may not behave differently with respect to the drivers or the manner in which they form their value perceptions. It is from these perspectives that our proposed method may provide maximum benefit.

Finite-mixture modeling

Finite-mixture modeling has become increasingly popular in the statistical and psychometric literatures in the past few years. The rapid growth of finite-mixture modeling stems from the importance of accounting for population heterogeneity in data. If data come from several populations, then conventional methods that ignore heterogeneity can result in misleading inferences. To illustrate the problems stemming from failure to treat heterogeneity, consider a simple regression model relating Sales to Advertising (i.e., Sales = a + b Adv). Suppose there are two *unobserved* segments of firms of approximately equal size. Suppose segment 1 operates in a declining or mature industry (e.g., tobacco industry) where the effect of advertising is weak (i.e., b_1 is close to zero) whereas segment 2 operates in a growing industry (e.g., internet) where b_2 is positive and large. Suppose we fail to recognize the heterogeneity and analyze the pooled data from a sample of firms drawn from both segments. Then, the aggregate analysis would result in an average b value that reflects neither segment. In addition, the estimated error variance would be larger because of the confounding of variance due to firm heterogeneity with random error variance. Finally, statistical inference could be distorted as the standard errors are functions of these estimates. Thus, aggregate analyses can result in misleading inferences when data are heterogeneous.

The finite-mixture methodology that we develop in this paper treats heterogeneity in simultaneous equation models by deriving segments of customers that are homogenous in their value drivers (i.e., members of a segment have common structural coefficients). Thus, our method simultaneously derives segments and segment-specific weights that relate perceived value and quality to their respective antecedents. Obviously, there are alternative approaches for handling heterogeneity. For example, if segments were known *a priori*, then a segment-level analysis would result in valid inferences. However, *a priori* segmentation based on firmographics may be infeasible or insufficient to explain differences in responses. Clustering the firms initially, and then estimating the model for each cluster is an alternative way for treating heterogeneity. This two-step approach, however, can result in different solutions depending on which algorithm is used for clustering. In addition, cluster analysis groups firms based on proximity. In contrast, the finite-mixture methodology is a single-step method that derives segments of customers that are homogenous in their responses or decision processes. Unlike cluster analysis, the finite-mixture modeling provides statistical tests that are useful for determining the number of segments and the statistical significance of the parameter estimates.

In addition to capturing heterogeneity in customer value modeling, the finite-mixture methodology could be applied in a wide range of strategy research areas. Here are few examples. Several studies in strategy research (e.g., on strategic groups) have found that firms pursuing the same strategy type do not necessarily achieve similar profitability results (see McGee and Thomas, 1986; White, 1986; Cool and Schendel, 1988; DeSarbo *et al*., 1990). This suggests that firms are heterogeneous in the effectiveness of their strategies. In this case, a segment is a group of firms that are homogeneous *not* in the strategies they pursue, but in their strategic responses. Similarly, the literature on geographical clusters argues that firms within a region tend to exhibit 'similar resources, cost structures, mental models, and competitive behavior' (Pouder and St. John, 1996: 1195). However, empirical evidence suggests that these firms are heterogeneous and achieve different levels of performance (Saxenian, 1994; McEvily and Zaheer, 1999). The finite-mixture methodology could be used to explain these differences. The literature on organization adoption of innovations argues that firms are heterogeneous in their adoption of new technologies: some are innovators always looking for new technologies and some are imitators waiting to learn from the innovators' experiences. Given historical adoption data by firms (see Majumdar and Venkataraman, 1998 for an example), the finite-mixture methodology could be used to derive segments of firms that are homogeneous in their adoption patterns.

AN EMPIRICAL APPLICATION

The CVA data for our application were obtained from a survey of commercial and industrial customers of a large electric utility company. Customers of this company received a notification letter one week prior to the interviewing to alert them that a call would be coming shortly concerning their customer opinions. Following this mailing, customers were contacted and a survey (entailing approximately 20 minutes per respondent) was administered via telephone interview. The survey and data collection procedure was conducted over a 15-month period. A total of 1509 cases were thus obtained for modeling purposes. We formulate a recursive simultaneous equation model employing two equations. The first equation specifies perceived value (VALUE) as a function of perceived price (PRICE) and perceived quality (QUAL). The second equation models perceived quality as a function of ratings of power reliability (PROD), preventative maintenance (MAINT), repair service (REPAIR), account representative (ACCT), technical support (TECH), customer service (SVC), record keeping (REC), and billing (BIL). A variety of firmographic and demographic variables were also collected including measures of sales region (REG1-REG6), account type (ACCTYPE1-ACCTYPE5), business type (BUSTYPE1-BUSTYPE4), respondent job type (PROF1-PROF4), presence of relations with other suppliers (RELATION), number of employees (NUMEMP), number of years as a customer (NUMYEARS), and a standardized measure of revenue coming from the particular account (REVENUES). The Appendix describes the empirical distribution for many of these firmographic variables appropriately disguised given the confidentiality of this data set.

The finite-mixture simultaneous equation model

Following the perceived value literature (see Chang and Wildt, 1994), we employ a two-equation, simultaneous equation approach to model the process of perceived value formation. The first equation relates perceived value to perceived price and perceived quality; the second equation relates perceived quality to perceived service attributes.[1]

As discussed previously, a major omission in previous research on perceived value has been the failure to account for customer heterogeneity in the integration of the underlying dimensions of value. We capture customer heterogeneity in this process through a finite-mixture approach (cf. Jedidi *et al.*, 1996) which derives segments of customers who are homogeneous in terms of their response parameters. Let i index customers ($i = 1, \ldots, N$) and g denote membership in a (*a-priori* unknown) segment ($g = 1, \ldots, G$). Conditional on membership in segment g, we postulate the following recursive simultaneous equation model:[2]

$$\begin{aligned}
\text{VALUE}_i|\text{g} &= \gamma_{10}^g + \beta_{12}^g \text{QUAL}_i + \gamma_{11}^g \text{PRICE}_i + \varepsilon_{1i}^g \\
\text{QUAL}_i|\text{g} &= \gamma_{20}^g + \gamma_{21}^g PROD_i + \gamma_{22}^g MAINT_i \\
&\quad + \gamma_{23}^g REPAIR_i + \gamma_{24}^g ACCT_i \\
&\quad + \gamma_{25}^g TECH_i + \gamma_{26}^g \text{SVC}_i + \gamma_{27}^g \text{REC}_i \\
&\quad + \gamma_{28}^g \text{BIL}_i + \varepsilon_{2i}^g,
\end{aligned} \tag{1}$$

where γ_{10}^g and γ_{20}^g are intercept parameters, γ_{11}^g is a parameter that measures the impact of price on value, β_{12}^g is a parameter that captures the simultaneity between perceived value and perceived quality, and $\gamma_{21}^g, \ldots, \gamma_{28}^g$ are parameters that reflect the effects of product and service attributes on perceived quality. We expect γ_{11}^g to be positive, whereas β_{12}^g to be negative. ε_{1i}^g and ε_{2i}^g are error terms that jointly follow a bivariate normal distribution with zero mean vector and covariance matrix:

$$\Psi_g = \begin{bmatrix} \Psi_{11}^g & \Psi_{12}^g \\ \Psi_{12}^g & \Psi_{22}^g \end{bmatrix}, \tag{2}$$

where ψ_{11}^g and ψ_{22}^g are the variances of the error terms, and ψ_{12}^g is the covariance between ε_{1i}^g and ε_{2i}^g. The covariance term captures the residual correlation between Value and Quality due, for example, to omitted variables that affect both of these variables. See Figure 1 for a graphical summary of the recursive simultaneous equation model postulated.

Before proceeding to model estimation, it is necessary to establish that this specified finite-mixture

[1] As per an anonymous reviewer suggestion, we also included price as an additional variable in the quality equation. Our empirical estimation, however, resulted in an insignificant price coefficient in all the segments. This suggests that price may not be an indicator of quality in the electric utility industry.

[2] For ease of exposition, we assume a linear relationship between Value and its antecedents: Quality and Price. We test for different functional forms (e.g., subtractive and ratio) later in this section.

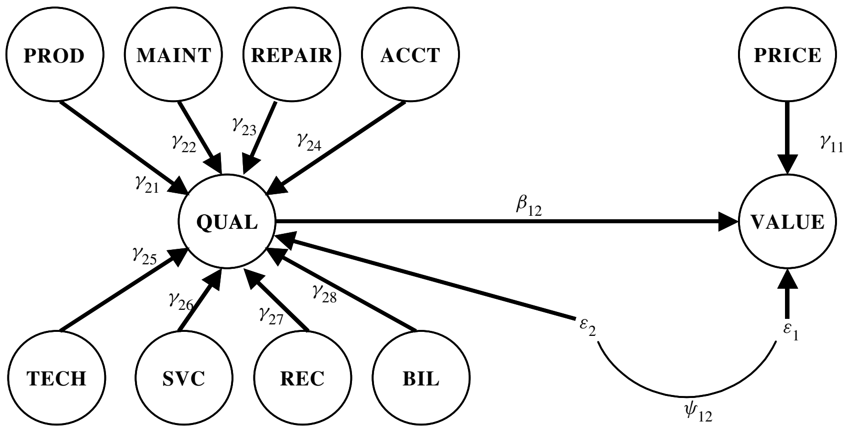

Figure 1. Theoretical model for the customer value study

simultaneous equation model is identified. Jedidi, Jagpal, and DeSarbo (1997a, b) have demonstrated that finite mixture of structural equation models are identified provided that the structural equation model is identified for known segments and the data (within segment) follow multivariate normal distributions. As we indicate below, our model satisfies both conditions and is therefore identified. First, this model is identified for known segments based on the sufficient *rank* condition (see Bollen, 1989:98). Second, we explicitly make the assumption that the error vector $\varepsilon_{ig} = \begin{bmatrix} \varepsilon_{1i}^g \\ \varepsilon_{2i}^g \end{bmatrix}$ follows a bivariate normal distribution.

Estimation

Let $y_i|g = \begin{bmatrix} VALUE_i|g \\ QUAL_i|g \end{bmatrix}$ denote the joint vector of endogenous variables conditional on membership in segment g. Then its conditional mean vector is defined by:

$$\mu_{ig} = \begin{bmatrix} \gamma_{10}^g + \beta_{12}^g QUAL_i + \gamma_{11}^g PRICE_i \\ \gamma_{20}^g + \gamma_{21}^g PRD_i + \gamma_{22}^g MAINT_i \\ +\gamma_{23}^g REPAIR_i + \gamma_{24}^g ACCT_i \\ +\gamma_{25}^g TECH_i + \gamma_{26}^g SVC_i \\ +\gamma_{27}^g REC_i + \gamma_{28}^g BIL_i \end{bmatrix} \quad (3)$$

and its conditional covariance matrix is Ψ_g. By assumption $y_i|g$ follows a conditional bivariate normal distribution. Hence the unconditional distribution of the observed vector $y_i|g$ is a finite mixture of these distributions. That is:

$$\mathbf{y}_i \sim \sum_{g=1}^{G} w_g f_g(\mathbf{y}_i|\boldsymbol{\mu}_{ig}, \boldsymbol{\Psi}_g), \quad (4)$$

where $w = (w_1, \ldots, w_G)'$ is the vector of the G mixing proportions such that $w_g > 0$ and $\sum_{g=1}^{G} w_g = 1$, and $f_g(.)$ is the bivariate normal density function. The likelihood function for a sample $(y_1 \ldots, y_N)'$ of N randomly drawn observations is:

$$L = \prod_{i=1}^{N} \left[\sum_{g=1}^{G} w_g |2\pi \boldsymbol{\Psi}_g|^{-1/2} \exp[-1/2(\mathbf{y}_i - \boldsymbol{\mu}_{ig})' \times \boldsymbol{\Psi}_g^{-1}(\mathbf{y}_i - \boldsymbol{\mu}_{ig})] \right]. \quad (5)$$

One now maximizes L (or Ln L) with respect to the free parameters β_{12}^g, $\boldsymbol{\Psi}_g$, $\boldsymbol{\Gamma}_g = (\gamma_{10}^g, \gamma_{11}^g, \gamma_{20}^g, \ldots, \gamma_{28}^g)'$, and $\mathbf{w}$ given the sample data $(y_1 \ldots, y_N)'$ while taking into account the constraints on $\mathbf{w}$ and $|\boldsymbol{\Psi}_g| > 0$ for all g.

We use a modified EM algorithm (Dempster, Laird, and Rubin, 1977) to maximize the likelihood function. This method is suited for models that deal with unobserved data (e.g., segment membership). The E-M method maximizes the complete data likelihood function (formed by assuming that segment membership is assumed to be known) by iterating between an Expectation step and a Maximization step until convergence. In the E-step, the segment memberships are estimated by their expected values given provisional estimates for $\boldsymbol{\Psi}_g$, $\boldsymbol{\Gamma}_g$, β_{12}^g, and $\mathbf{w}$. In the M-step, the provisional estimates for $\boldsymbol{\Psi}_g$, $\boldsymbol{\Gamma}_g$, β_{12}^g, and $\mathbf{w}$ are updated in light of the newly estimated values of segment memberships (cf. Titterington, Smith, and Makov, 1985). Within any iterate, one can use the estimates for

$\mathbf{\Psi}_g$, $\mathbf{\Gamma}_g$, β_{12}^g and $\mathbf{w}$ to compute the posterior probability of membership:

$$\hat{\mathrm{P}}_{ig} = \hat{\mathrm{w}}_g \mathrm{f}_g(\mathbf{y}_i|\hat{\boldsymbol{\mu}}_{ig}, \hat{\mathbf{\Psi}}_g) / \sum_{k=1}^{G} \mathrm{w}_k \mathrm{f}_k(\mathbf{y}_i|\hat{\boldsymbol{\mu}}_{ik}, \hat{\mathbf{\Psi}}_k), \tag{6}$$

to assign each of the individual observations in each of the G segments. We compute the asymptotic standard errors using the inverse of the empirical information matrix (see Meilijson 1989). Details of the algorithm are available from the authors upon request.

We infer the appropriate number of segments G by running the estimation procedure for varying number of segments. We choose the solution that corresponds to the minimum value of Bozdogan's (1987) Consistent AIC criterion:

$$\mathrm{CAIC}_G = -2\mathrm{LnL}_G + \mathrm{M}_G \mathrm{Ln}(\mathrm{N}+1), \tag{7}$$

where M_G is the number of free parameters in a G-segment model. Note, as CAIC is an increasing function of the number of parameters M_G, it penalizes models with more parameters and with higher number of segments. We use an entropy-based measure E_G to assess the quality of separation among the segments (see DeSarbo and Wedel 1994). Specifically, E_G is defined by:

$$\mathrm{E}_G = 1 - \left[\sum_{i=1}^{N}\sum_{g=1}^{G} -\hat{\mathrm{P}}_{ig} \ln \hat{\mathrm{P}}_{ig} / (\mathrm{N} \ln \mathrm{G})\right]. \tag{8}$$

This measure is bounded between 0 and 1. A value close to 0 indicates that the posterior probabilities are not well separated (i.e., it is difficult to classify observation accurately into distinct segments). In contrast, a value equal to 1 indicates a discrete partitioning of the sample (i.e., each observation is accurately classified in one and only one segment).

Our model provides several managerial benefits over previous models (e.g., Chang and Wildt, 1994). First, it allows managers to segment customers based on their value integration process. As segments have different value drivers, managers can devise different strategies for these segments. In addition, by relating customer characteristics to segment memberships, managers can optimally target and reach these segments. Clearly, as the statistical literature on heterogeneity attests, an aggregate analysis that ignores customer heterogeneity can result in misleading inferences (e.g., biased estimates, wrong signs, incorrect standard errors) and can therefore provide a distorted picture of the market place. Finally, as will be discussed later, our model permits the testing of different value integration forms (i.e., subtractive and ratio forms) while accounting for customer heterogeneity.

Results

Table 1 presents the various summary statistics and goodness of fit indices for g = 1,2,3,4 market segments. According to the CAIC criterion, G = 3 segments appears to be the most parsimonious solution. Notice how the G = 1 aggregate solution is rejected in this analysis suggesting sufficient sample heterogeneity to warrant further disaggregation. Furthermore, notice that the G = 4 segment solution is rejected even though it has a better log likelihood value (ln L). This is because the CAIC statistic penalizes models with larger number of parameters. In other words, the marginal gain of 7.59 (i.e., 2841.43–2833.84) likelihood points is not sufficient to warrant the inclusion of an additional 16 (i.e., 63–47) parameters. The entropy measure, E_G, for the three-segment solution is 0.622. This indicates that the derived conditional centroids for the three segments are reasonably well separated. Table 2 depicts the one - (aggregate solution) and three - segment solutions in terms of coefficients, standard errors (in parentheses), and mixing proportions (size of the segments). Note that the signs of the significant parameters are all in the expected direction in that perceived value is related positively to perceived quality (and all service attribute variables) but is associated negatively with perceived price. For the aggregate solution, virtually all coefficients are significant (except customer service) at $p < 0.05$. Here, quality, price, and power reliability are the most important aspects of this recursive system of

Table 1. Summary statistics for model selection results

G	Number of Free Parameters	Ln L	CAIC	Entropy
1	15	−3450.38	7025.56	—
2	31	−3007.95	6273.79	0.679
3	47	−2841.43	6073.86*	0.622
4	63	−2833.84	6191.80	0.577

* Denotes solution with minimum CAIC

equations. Perceived quality appears to have one and a half times the impact on perceived value as compared to perceived price at this aggregate level of analysis, whereas power reliability possesses nearly three times the impact of any other performance/service attribute on perceived quality.

Contrasting this aggregate solution with the three-segment solution in Table 2 reveals several interesting insights. Market segment one, the largest segment containing 43.6% of the sample, has a very different response set of coefficients than that of the aggregate solution discussed above. Here, we see that perceived value is driven by perceived quality, and not perceived price. Power reliability, record keeping, and customer service are the only significant coefficients in the associated perceived quality equation. Market segment two is the smallest segment containing 22.8% of the sample. It is interesting to note here that both perceived quality and perceived price impact perceived value with roughly the same magnitude in the first equation for this segment. Here too, power reliability dominates the impact on perceived quality, but there are sizable significant effects for preventative maintenance, repair service, account representative, and billing. Finally, market segment three, accounting for 33.6% of the sample, possesses response coefficients most similar to the aggregate equations. Here, the impact of perceived quality is about one and one-half times that of perceived price on perceived value in the first equation; and, both effects are significant. While power reliability has the highest impact on perceived quality in the second equation for this segment, significant effects also exist for preventative maintenance, repair service, account

Table 2. Parameter estimates for the aggregate and three-segment solution

The Value Equation	Aggregate Solution	The Three-Segment Solution: Segment 1	Segment 2	Segment 3
Intercept	0.000[1]	0.384*	−0.298*	−0.115*
		(0.013)	(0.029)	(0.049)
Quality	0.584*	0.368*	0.498*	0.621*
	(0.032)	(0.059)	(0.039)	(0.049)
Price	−0.399*	−0.009	−0.481*	−0.470*
	(0.020)	(0.005)	(0.022)	(0.039)
The Quality Equation		Segment 1	Segment 2	Segment 3
Intercept	0.000[1]	0.033	−0.325*	0.328*
		(0.029)	(0.033)	(0.035)
Power Reliability	0.389*	0.179*	0.286*	0.511*
	(0.021)	(0.026)	(0.033)	(0.037)
Preventative Maintenance	0.110*	0.018	0.173*	0.136*
	(0.021)	(0.013)	(0.031)	(0.040)
Repair Service	0.087*	0.001	0.106*	0.137*
	(0.021)	(0.012)	(0.033)	(0.039)
Account Representative	0.154*	0.026	0.131	0.163*
	(0.019)	(0.13)	(0.031)	(0.034)
Technical Support	0.101*	0.053	0.025	0.129*
	(0.019)	(0.14)	(0.030)	(0.032)
Customer Service	0.031	0.053*	0.037	−0.001
	(0.020)	(0.014)	(0.030)	(0.035)
Record Keeping	0.051*	0.037*	0.077*	0.024
	(0.020)	(0.013)	(0.030)	(0.035)
Billing	0.108*	−0.009	0.091*	0.179*
	(0.020)	(0.012)	(0.031)	(0.037)
Mixing Proportions	—	0.436	0.228	0.336

[1] The intercepts are zero in the aggregate solution since all variables were standardized to zero mean and unit variance
* $p < 0.05$

representative, technical support, and billing. Thus, one may visualize how the aggregate solution masks the more representative disaggregate three-segment solution and the differences in the coefficient values across the three market segments.

Another important aspect of the analysis concerns an inspection of the estimated intercepts and a comparison of the means for each segment for the various dependent and independent variables in the two equations. Table 3 presents the means of these variables across segments. Interpreting these results together with the estimated intercepts provides additional important information as to how these market segments differ. Market segment one possesses the highest positive intercept in the perceived value equation, as well as the highest mean on this dependent variable across the three segments. Members of this market segment evidently perceive the highest value overall from this electric utility company and its services. Yet, the means on perceived quality and perceived price are not the highest across the three segments! Market segment two possesses the lowest means on all variables (and negative intercepts in the two equations) indicating a general sense of unhappiness amongst the members of this market segment. Given deregulation in this industry, they may be the most likely to switch suppliers in the upcoming years. Finally, market segment three possesses the highest means for perceived quality and perceived price, yet the mean (and intercept) for perceived value is negative, indicating perhaps that members of this segment may be responsive to other unobserved factors (in addition to perceived quality and price) in their perceived value formation.

Table 3. Variable means across segments[1]

Variable	Segment 1	Segment 2	Segment 3
VALUE	0.407	−0.743	−0.024
PRICE	0.046	−0.277	0.129
QUALITY	0.056	−0.457	0.238
POWER RELIABILITY	0.060	−0.169	0.037
PREVENTATIVE MAINTENANCE	0.121	−0.187	−0.030
REPAIR SERVICE	0.096	−0.200	0.011
ACCOUNT REPRESENTATIVE	0.014	−0.100	0.050
TECHNICAL SUPPORT	−0.004	−0.104	0.077
CUSTOMER SERVICE	0.062	−0.144	0.018
RECORD KEEPING	0.059	−0.082	−0.021
BILLING	0.087	−0.149	−0.012

[1] All variables were standardized to zero mean and unit variance prior to computing the segment means.

Finally, a useful feature of our proposed methodology is the ability to profile the derived segments vis a vis posterior analysis using the customers' background firmographic variables. Table 4 presents the results from stepwise logistic regression analyses to examine how well these segments can be differentiated on the basis of the firmographics that were also collected in this study. Here, the logits of the estimated posterior probabilities of segment membership derived directly from the estimation were utilized as the dependent variable. As shown in Table 4, Segment one members tend not to be from sales region 5, be of business type 4, newer customers of this electric utility company, and are typically smaller customers. Segment two members tend not to come from sales region 2, nor be of business type 4. Finally, segment three members tend to arise from sales regions 2 and 3, not be of business type 4, and are larger customers of this electric utility. Note that all three logistic regression equations are significant at the $p < 0.05$ level. One can likewise inspect Table 3 for differences in mean values to better portray these three very different market segments.

Testing alternative functional forms

Given that the literature has documented both the subtractive and ratio functions for perceived

Table 4. Logistic regression results for posterior analysis

Variable	Segment 1	Segment 2	Segment 3
INTERCEPT	−1.47	−3.48***	−1.18
REG2		−0.43**	1.25**
REG3			0.73*
REG5	−2.10**		
BUSTYPE4	2.91*	−0.760*	−1.66**
NUMYEARS	−0.05*		
REVENUES	−0.27*		0.23**
F	3.47***	3.28**	2.88**

*** Significant at 0.01 level
** Significant at 0.05 level
* Significant at 0.10 level

quality and perceived price in the formation of perceived value in the first equation, we chose to run such specifications for both the aggregate and three segment model, and compared the corresponding goodness of fit tests. We also altered the first equation in terms of utilizing single parameters for the difference or ratio of perceived quality and price vs. the presented solution where separate parameters were estimated separately for perceived quality and perceived price in the difference form. Table 5 presents the summary fit measures for these various specifications. In all cases, the presented solution (separate parameters and differencing) dominated (i.e., had minimum CAIC) all other specifications for this data set—a finding which confirms the empirical results of Hagerty (1978) and Levin and Johnson (1984). Similarly, the single parameter (in first equation) subtractive solution dominates the ratio solution.

DISCUSSION

In the above section, we have provided an alternative CVA methodology for understanding the drivers of perceived value as well as its relationship with its various components including perceived quality, perceived price, and perceptions of product/service attribute performance/information. This model accommodates sample heterogeneity on a market segment level whereby estimates of the number of market segments, their sizes, and the composition of such segments are obtained simultaneously with estimates of each segment's model coefficients. The market segments are derived on the basis of structural differences in the integration of quality and price perceptions and from various attribute performance ratings. Posterior analysis allows the profiling of the derived market segments in terms of firmographic variables for strategic actionability.

The application of this approach in an actual CVM study has yielded results that benefit both the researcher and practitioner. First, by making use of a relatively large (1509 observations) commercial dataset, we demonstrate that an aggregate analysis, involving the modeling of perceived value on perceived quality and perceived price ignoring sample heterogeneity, offers an incomplete and potentially misleading view of the market. For instance, the aggregate solution in our case led to the conclusion that *both* quality and price are significant ($p < 0.05$) antecedents of perceived value. In reality, the market is comprised of three segments, all of which ascribe different importances to the perceived value antecedents. Importantly, the largest segment (44% of the sample) is found to significantly base their value perceptions solely on perceived quality, and is seemingly oblivious of price. (Given the nature of the "product" category, viz. electric utility, this may not be a surprising finding).

Aside from deriving a quality-driven segment, we have uncovered the presence of two other segments, both of which significantly relied on perceived quality and price, but *differed in the relative importances* that they assigned to each in their value perceptions. Additionally, the heterogeneity embedded in our model structure extends beyond just quality and price. Consistent with Porter's "buyer value chain" notion, we have allowed for different interpretations of perceived quality as well (i.e., aside from value) among subjects relative to the physical characteristics of the "product." Consequently, our model may be viewed as capturing two sources of heterogeneity in the data: first, inter-segment differences due to composition of perceived quality; and, second, inter-segment differences in the integration of perceived quality and price.

The final contribution of the proposed approach is that it has permitted alternative functional forms

Table 5. Summary statistics for testing alternative value function specifications

Model	Value Function	Number of Parameters	Ln L	CAIC	Entropy
Aggregate	Present	15	−3450.38	7025.56	—
	Subtractive	14	−3458.60	7033.68	—
	Ratio	14	−3537.16	7190.80	—
Three-Segment	Present	47	−2841.43	6073.86	0.622
	Subtractive	44	−3253.96	6873.98	0.397
	Ratio	44	−3355.78	7077.61	0.400

of perceived value to be formulated and tested resulting in the exploration of the issue of integration rule involving perceived quality and price. Like previous authors, we find that the subtractive integration rule (combining quality and price) dominated the proportionate rule.

Managerial implications

There are three principal potential managerial benefits of the proposed methodology. First, this approach provides a convenient tool that accomplishes (through the *same* procedure) the dual objectives of market segmentation and customer value analysis. By being able to estimate segment-specific response coefficients for the antecedents of value, i.e., quality and price, as well as the determinants of quality, a manager can know which segment to target and what characteristics to improve to communicate better value. For example, the largest derived market segment ("Hi Valuers"), which derived the highest perceived value from this electric utility company, viewed quality as the sole determinant of value and power reliability as the most significant attribute. Strategically speaking, reliable power supply (i.e., no outages) is what must be stressed with these customers. Members of this segment appear to be relatively price inelastic and this provides an opportunity for increased revenue generation for the firm.

Second, by considering heterogeneity among buyers, our CVA approach reveals market dynamics in interesting ways. Through the use of post-hoc analysis using firm-level variables, we can "profile" the identified segments, that further assists the manager. Thus, we find that the first segment is composed of the more recent and smaller customers of this company in sales region 5 and of business type 4. The second market segment (labeled "Negatives") appeared to provide negative perceptions on virtually all factors, which suggests that the members of this segment may be most vulnerable to switching given that this industry is deregulated. These buyers seem to be spread across the other sales regions and business types that are different from the members of segment one. Lastly, market segment three (labeled "Qualities") is comprised of the larger and older customers of this electric utility company. These members are typically from sales regions 2 and 3, are spread over business types that are different from 4, and have the highest perceived quality and price average scores of any of the three segments.

Finally, the strategic interest in our approach can be appreciated in the context of recent developments in E-Business and the Internet. When competitive rivalry among websites (e.g., Priceline versus Travelocity) is often viewed as a battle of "value propositions," a method such as ours allows firms to assess the feasibility of their online business models by teasing out what it is that customers *actually* value. It is thus possible to account for the effects that the salient characteristics of Internet retailers (like convenience, low price, service, and selection) have on customer-perceived value, particularly when individual differences are explicitly accounted for. Most of all, we allow the "data to do the talking" insofar as which attributes are important to which groups of customers, instead of imposing some prior and arbitrary cluster structure that may not be appropriate.

Limitations and future research

There are some obvious limitations of our study that should offer opportunities for further research. First, we have focused on perceived quality and price as being the key variables in perceived value formation, which is a view consistent with many earlier authors (e.g., Monroe, 1990). Future research may include an even broader set of variables. Second, our chosen product category for model estimation, an electric utility, is especially idiosyncratic in terms of regulation, lack of competition, and fairly narrow and well-defined consumer expectation set. Consequently, the results reported from calibrating the model should not be held to apply to other categories since the results of customer value analysis are necessarily considered to hold true for a given product/service category.

A number of interesting methodological avenues for future research also follow from our formulation of perceived value. Methodologically, it might prove useful to devise a mixture model scenario where segments are explicitly derived in terms of alternative response models for perceived value in the first equation. Here, for example, this could be implemented by allowing for subtractive and ratio modes of response for different segments in how perceived quality and perceived price relate to perceived value. The objective would be to partition the sample according to how formulations of perceived value were formulated, much along the suggestions of White and Truly (1989). Another methodological extension would be to explicitly embed the firmographic variables in the analysis by reparameterizing the mixing proportions as functions of them as performed in Dayton and MacCready (1988). Finally, modifying the existing methodology to explicitly address client level constraints and prior knowledge as in DeSarbo and Grisaffe (1998) would make the derived market segments more managerially relevant.

REFERENCES

Anderson JC, Narus JA. 1998. Business marketing: understanding what customers value. *Harvard Business Review* **76**(6), 53–61.

Bollen KA. 1989. *Structural Equations with Latent Variables*. Wiley: New York.

Bozdogan H. 1987. Model Selection and Akaike's information criteria (AIC): the general theory and its analytical extensions. *Psychometrika* **52**: 345–370.

Chang T, Wildt AR. 1994. Price, product information, and purchase intention: an empirical study. *Journal of the Academy of Marketing Science* **22**: 16–27.

Cool K, Schendel DE. 1988. Performance differences among strategic group members. *Strategic Management Journal* **9**(3): 207–223.

Dayton CM, MacCready GB. 1988. Concomitant variables latent class models. *Journal of the American Statistical Society* **83**: 173–178.

Dempster AP, Laird NM, Rubi DB. 1977. Maximum likelihood from incomplete data via the E-M algorithm. *Journal of the Royal Statistical Society* **39**: 1–38.

DeSarbo WS, Grisaffe DB. 1998. Combinatorial approaches to constrained market segmentation: an application to industrial market segmentation. *Marketing Letters* **9**: 115–134.

DeSarbo WS, Wedel M. 1994. A review of recent developments in latent class regression models. In *Handbook of Marketing Research*, Bagozzi RP (ed.). Blackwell: New York; 352–388.

DeSarbo WS, Jedidi K, Cool K, Schendel DE. 1990. Simultaneous multidimensional unfolding and cluster analysis. *Marketing Letters* **2**: 129–146.

Drucker PF. 1985. *Innovation and Entrepreneurship*. Harper and Row: New York.

Gale BT. 1994. *Managing Customer Value*. Free Press: New York.

Hagerty MR. 1978. Model testing techniques and price-quality tradeoffs. *Journal of Consumer Research* **5**: 194–205.

Jacoby J, Olson JC. 1977. Consumer response to price: an attitudinal, information processing perspective. In *Moving Ahead with Attitude Research*, Wind Y, Greenberg P (eds.). American Marketing Association: Chicago IL; 73–86.

Jedidi K, Jagpal H, DeSarbo WS. 1997a. Semi-parametric structural equation models for response-based segmentation and unobserved heterogeneity. *Marketing Science* **16**: 39–59.

Jedidi K, Jagpal H, DeSarbo WS. 1997b. STEMM: a general finite mixture structural equation model. *Journal of Classification* **14**: 23–50.

Jedidi K, Ramaswamy V, DeSarbo WS, Wede M. 1996. On estimating finite mixtures of multivariate regression and simultaneous equation models. *Structural Equation Modeling: A Multidisciplinary Journal* **3**: 266–289.

Levin IP, Johnson RD. 1984. Estimating price-quality tradeoffs using comparative judgments. *Journal of Consumer Research* **11**: 593–600.

Majumdar SK, Venkatarama S. 1998. Network effects and the adoption of new technology: evidence from the U.S. telecommunications industry. *Strategic Management Journal* **19**(11): 1045–1062.

McEvily W, Zaheer A. 1999. Bridging ties: a source of firm heterogeneity in competitive capabilities. *Strategic Management Journal* **20**(12): 1133–1156.

McGee J, Thomas H. 1986. Strategic groups: theory, research and taxonomy. *Strategic Management Journal* **7**(2): 141–160.

Meilijson I. 1989. A fast improvement to the EM algorithm on its own terms. *Journal of the Royal Statistical Society* **51**: 127–138.

Monroe KB. 1990. *Pricing: Making Profitable Decisions* (2nd edn). McGraw Hill: New York.

Nayyar PR. 1995. Stock market reactions to customer service changes. *Strategic Management Journal* **16**(1): 39–53.

Olson JC, Reynolds TJ. 1983. Understanding consumers' cognitive structures: implications for advertising strategy. In *Advertising and Consumer Psychology*, Persy L, Woodside A (eds). Lexington Books: Lexington, MA; 143–162.

Porter M. 1985. *Competitive Advantage*. Free Press: New York.

Porter M. 1998. *Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press: New York.

Pouder R, St. John CH. 1996. Hot spots and blind spots: geographical clusters of firms and innovation. *Academy of Management Review* **21**: 1192–1225.

Prahalad CK, Hamel G. 1994. Strategy as a field of study: Why search for a new paradigm? *Strategic Management Journal*, Summer Special Issue **15**: 5–16.

Prahalad CK, Ramaswamy V. 2000. Co-opting customer competence. *Harvard Business Review* **78**(1): 79–87.

Ramirez R. 1999. Value co-production: intellectual origins and implications for practice and research. *Strategic Management Journal* **20**(1): 49–65.

Reichheld FF. 1996. *The Loyalty Effect: The Hidden Force behind Growth, Profits, and Lasting Value*. Harvard Business School Press: Boston, MA.

Saxenian A. 1994. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press: Cambridge, MA.

Sinha I, DeSarb WS. 1998. An integrated approach toward the spatial modeling of perceived customer value. *Journal of Marketing Research* **35**: 236–249.

Slater SF, Narve JC. 1998. Customer-led and market-oriented: let's not confuse the two. *Strategic Management Journal* **19**(10): 1001–1006.

Titterington DM, Smith AFM, Makov UE. 1985. *Statistical Analysis of Finite Mixture Distributions*. Wiley: New York.

White JD, Trul EL. 1989. Price-quality integration in warranty evaluation. *Journal of Business Research* **19**: 109–125.

White R. 1986. Generic business strategies, organizational context, and performance: an empirical investigation. *Strategic Management Journal* **7**(3): 217–231.

Zeithaml VA. 1988. Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing* **52**: 2–22.

APPENDIX

Empirical distributions for firmographic variables

Sales Region

Region	Frequency	Percent
1	383	25.4
2	359	23.8
3	321	21.3
4	88	5.8
5	167	11.1
6	191	12.6

Account Type

Account Type	Frequency	Percent
1	27	1.8
2	309	20.5
3	773	51.2
4	220	14.6
5	180	11.9

Business Type

Type	Frequency	Percent
Manufacturing	343	22.7
Non-Manufacturing	1166	77.3

Respondent Title

Respondent	Frequency	Percent
Senior Manager	431	28.6
Middle Manager	516	34.2
Technical	489	32.4
Other	73	4.8

Continuous Firmographic Variables

Variable	Mean	Standard Deviation
Number of Employees	491.92	742.02
Number of Years a Customer of Firm	27.3	16.79
Percentage Dealing with Other Suppliers	16.0%	0.367