

Return on Marketing: Using Customer Equity to Focus Marketing Strategy

The authors present a unified strategic framework that enables competing marketing strategy options to be traded off on the basis of projected financial return, which is operationalized as the change in a firm's customer equity relative to the incremental expenditure necessary to produce the change. The change in the firm's customer equity is the change in its current and future customers' lifetime values, summed across all customers in the industry. Each customer's lifetime value results from the frequency of category purchases, average quantity of purchase, and brand-switching patterns combined with the firm's contribution margin. The brand-switching matrix can be estimated from either longitudinal panel data or cross-sectional survey data, using a logit choice model. Firms can analyze drivers that have the greatest impact, compare the drivers' performance with that of competitors' drivers, and project return on investment from improvements in the drivers. To demonstrate how the approach can be implemented in a specific corporate setting and to show the methods used to test and validate the model, the authors illustrate a detailed application of the approach by using data from the airline industry. Their framework enables what-if evaluation of marketing return on investment, which can include such criteria as return on quality, return on advertising, return on loyalty programs, and even return on corporate citizenship, given a particular shift in customer perceptions. This enables the firm to focus marketing efforts on strategic initiatives that generate the greatest return.

The Marketing Strategy Problem

Top managers are constantly faced with the problem of how to trade off competing strategic marketing initiatives. For example, should the firm increase advertising, invest in a loyalty program, improve service quality, or

none of the above? Such high-level decisions are typically left to the judgment of the chief marketing or chief executive officers, but these executives frequently have little to base their decisions on other than their own experience and intuition. A unified, data-driven basis for making broad, strategic marketing trade-offs has not been available. In this article, we propose that trade-offs be made on the basis of projected financial impact, and we provide a framework that top managers can use to do this.

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Financial Accountability

Although techniques exist for evaluating the financial return from particular marketing expenditures (e.g., advertising, direct mailings, sales promotion) given a longitudinal history of expenditures (for a review, see Berger et al. 2002), the approaches have not produced a practical, high-level model that can be used to trade off marketing strategies in general. Furthermore, the requirement of a lengthy history of longitudinal data has made the application of return on investment (ROI) models fairly rare in marketing. As a result, top management has too often viewed marketing expenditures as short-term costs rather than long-term investments and as financially unaccountable (Schultz and Gronstedt 1997). Leading marketing companies consider this problem so important that the Marketing Science Institute has established its highest priority for 2002–2004 as “Assessing Marketing Productivity (Return on Marketing) and Marketing Metrics.” We propose that firms achieve this financial accountability by considering the effect of strategic marketing expenditures on their customer equity and by relating the improvement in customer equity to the expenditure required to achieve it.

Customer Equity

Although the marketing concept has reflected a customer-centered viewpoint since the 1960s (e.g., Kotler 1967), marketing theory and practice have become increasingly customer-centered during the past 40 years (Vavra 1997, pp. 6–8). For example, marketing has decreased its emphasis on short-term transactions and has increased its focus on long-term customer relationships (e.g., Håkansson 1982; Storbacka 1994). The customer-centered viewpoint is reflected in the concepts and metrics that drive marketing management, including such metrics as customer satisfaction (Oliver 1980), market orientation (Narver and Slater 1990), and customer value (Bolton and Drew 1991). In recent years, customer lifetime value (CLV) and its implications have received increasing attention (Berger and Nasr 1998; Mulhern 1999; Reinartz and Kumar 2000). For example, brand equity, a fundamentally product-centered concept, has been challenged by the customer-centered concept of customer equity (Blattberg and Deighton 1996; Blattberg, Getz and Thomas 2001; Rust, Zeithaml, and Lemon 2000). For the purposes of this article, and largely consistent with Blattberg and Deighton (1996) but also given the possibility of new customers (Hogan, Lemon, and Libai 2002), we define *customer equity* as the total of the discounted lifetime values summed over all of the firm's current and potential customers.¹

Our definition suggests that customers and customer equity are more central to many firms than brands and brand equity are, though current management practices and metrics do not yet fully reflect this shift. The shift from product-centered thinking to customer-centered thinking implies the need for an accompanying shift from product-based strategy to customer-based strategy (Gale 1994; Kordupleski, Rust, and Zahorik 1993). In other words, a firm's strategic opportunities might be best viewed in terms of the firm's opportunity to improve the drivers of its customer equity.

Contribution of the Article

Because our article incorporates elements from several literature streams within the marketing literature, it is useful to point out the relative contribution of the article. Table 1 shows the contribution of this article with respect to several streams of literature that influenced the return on marketing conceptual framework. Table 1 shows related influential literature streams and exemplars of the stream, and it highlights key features that differentiate the current effort from previous work. For example, strategic portfolio models, as Larreché and Srinivasan (1982) exemplify, consider strategic trade-offs of any potential marketing expenditures. However, the models do not project ROI from specific expenditures, do not model competition, and do not model the behavior of individual customers, their customer-level brand switching, or their lifetime value. Our model adds to the

¹For expositional simplicity, we assume throughout much of the article that the firm has one brand and one market, and therefore we use the terms "firm" and "brand" interchangeably. In many firms, the firm's customer equity may result from sales of several brands and/or several distinct goods or services.

strategic portfolio literature by incorporating those elements.

Three related streams of literature involve CLV models (Berger and Nasr 1998), direct marketing–motivated models of customer equity (e.g., Blattberg and Deighton 1996; Blattberg, Getz, and Thomas 2001), and longitudinal database marketing models (e.g., Bolton, Lemon, and Verhoef 2004; Reinartz and Kumar 2000). Our CLV model builds on these approaches. However, the preceding models are restricted to companies in which a longitudinal customer database exists that contains marketing efforts that target each customer and the associated customer responses. Unless the longitudinal database involves panel data across several competitors, no competitive effects can be modeled. Our model is more general in that it does not require the existence of a longitudinal database, and it can consider any marketing expenditure, not only expenditures that are targeted one-to-one. We also model competition and incorporate purchases from competitors (or brand switching), in contrast to most existing models from the direct marketing tradition.

The financial-impact element of our model is foreshadowed by two related literature streams. The service profit chain (e.g., Heskett et al. 1994; Kamakura et al. 2002) and return on quality (Rust, Zahorik, and Keiningham 1994, 1995) models both involve impact chains that relate service quality to customer retention and profitability. The return on quality models go a step farther and explicitly project financial return from prospective service improvements. Following both literature streams, we also incorporate a chain of effects that leads to financial impact. As does the return on quality model, our model projects ROI. Unlike other models, our model facilitates strategic trade-offs of any prospective marketing expenditures (not only service improvements). We explicitly model the effect of competition—an element that does not appear in the service profit chain or return on quality models. Also different from prior research, our approach models customer utility, brand switching, and lifetime value.

Finally, we compare the current article with a recent book on customer equity (Rust, Zeithaml, and Lemon 2000) that focuses on broad managerial issues related to customer equity, such as building a managerial framework related to value equity, brand equity, and relationship equity. The book includes only one equation (which is inconsistent with the models in this article). Our article is a necessary complement to the book, providing the statistical and implementation details necessary to implement the book's customer equity framework in practice. The current work extends the book's CLV conceptualization in two important ways: It allows for heterogeneous interpurchase times, and it incorporates customer-specific brand-switching matrices. In summary, the current article has incorporated many influences, but it makes a unique contribution to the literature.

Overview of the Article

In the next section, on the basis of a new model of CLV, we describe how marketing actions link to customer equity and financial return. The following section describes issues in the implementation of our framework, including data options, model input, and model estimation. We then present

TABLE 1
Comparing the Return on Marketing Model with Existing Marketing Models

Type of Model	Exemplars	Strategic Trade-offs of Any Marketing Expenditures	ROI Modeled and Calculated?	Explicitly Models Competition?	Calculation of CLV?	Can Be Applied to Most Industries?	Net Present Value of Revenues and Costs?	Brand Switching Modeled at Customer Level?	Statistical Details?
Strategic portfolio	Larreché and Srinivasan (1982)	Yes	No	No	No	Yes	Yes	No	Yes
CLV	Berger and Nasr (1998)	No	No	No	Yes	No	Yes	No	Yes
Direct marketing: customer equity	Blattberg and Deighton (1996); Blattberg, Getz, and Thomas (2001)	No	Yes	No	Yes	Yes	Yes	No	Yes
Longitudinal database marketing	Bolton, Lemon, and Verhoef (2004); Reinartz and Kumar (2000)	Yes	Yes	No, unless panel data	Yes	No	Yes	No, unless panel data	Yes
Service profit chain	Heskett et al. (1994); Kamakura et al. (2002)	No	No	No	No	No	No	No	Yes
Return on quality	Rust, Zahorik, and Keiningham (1994, 1995)	No	Yes	No	No	Yes	Yes	No	Yes
Customer equity book	Rust, Zeithaml, and Lemon (2000)	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Return on marketing	Current paper	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

an example application to the airline industry, showing some of the details that arise in application, in testing and validating our choice model, and in providing some substantive observations. We end with discussion and conclusions.

Linking Marketing Actions to Financial Return

Conceptual Model

Figure 1 shows a broad overview of the conceptual model that we used to evaluate return on marketing. Marketing is viewed as an investment (Srivastava, Shervani, and Fahey 1998) that produces an improvement in a driver of customer equity (for simplicity of exposition, we refer to an improvement in only one driver, but our model also accommodates simultaneous improvement in multiple drivers). This leads to improved customer perceptions (Simester et al. 2000), which result in increased customer attraction and retention (Danaher and Rust 1996). Better attraction and retention lead to increased CLV (Berger and Nasr 1998) and customer equity (Blattberg and Deighton 1996). The increase in customer equity, when considered in relation to the cost of mar-

keting investment, results in a return on marketing investment. Central to our model is a new CLV model that incorporates brand switching.

Brand Switching and CLV

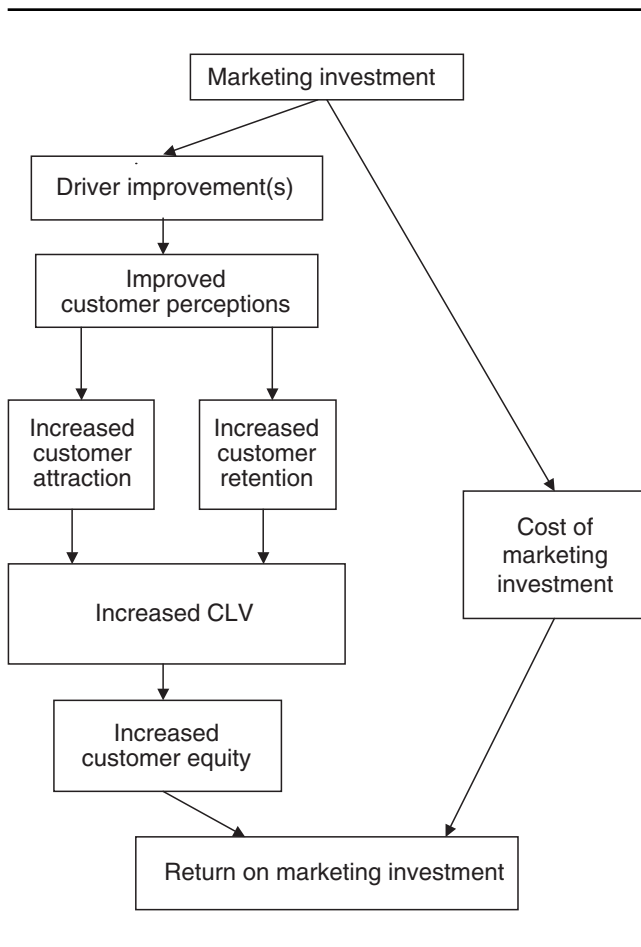
It has long been known that the consideration of competing brands is a central element of brand choice (Guadagni and Little 1983). Therefore, we begin with the assumption that competition has an impact on each customer's purchase decisions, and we explicitly consider the relationship between the focal brand and competitors' brands. In contrast, most, if not all, CLV models address the effects of marketing actions without considering competing brands. This is because data that are typically available to direct marketers rarely include information about the sales or preference for competing brands. Our approach incorporates information about not only the focal brand but competing brands as well, which enables us to create a model that contains both customer attraction and retention in the context of brand switching. The approach considers customer flows from one competitor to another, which is analogous to brand-switching models in consumer packaged goods (e.g., Massy, Montgomery, and Morrison 1970) and migration models (Dwyer 1997). The advantage of the approach is that competitive effects can be modeled, thereby yielding a fuller and truer accounting of CLV and customer equity.

When are customers gone? Customer retention historically has been treated according to two assumptions (Jackson 1985). First, the "lost for good" assumption uses the customer's retention probability (often the retention rate in the customer's segment) as the probability that a firm's customer in one period is still the firm's customer in the following period. Because the retention probability is typically less than one, the probability that the customer is retained declines over time. The implicit assumption is that customers are "alive" until they "die," after which they are lost for good. Models for estimating the number of active customers have been proposed for relationship marketing (Schmittlein, Morrison, and Columbo 1987), customer retention (Bolton 1998), and CLV (Reinartz 1999).

The second assumption is the "always a share" assumption, in which customers may not give any firm all of their business. Attempts have been made to model this by a "migration model" (Berger and Nasr 1998; Dwyer 1997). The migration model assigns a retention probability as previously, but if the customer has missed a period, a lower probability is assigned to indicate the possibility that the customer may return. Likewise, if the customer has been gone for two periods, an even lower probability is assigned. This is an incomplete model of switching because it includes purchases from only one firm.

In one scenario (consistent with the lost-for-good assumption) when the customer is gone, he or she is gone. This approach systematically understates CLV to the extent that it is possible for customers to return. In another scenario (consistent with the migration model), the customer may leave and return. In this scenario, customers may be either serially monogamous or polygamous (Dowling and Uncles

FIGURE 1
Return on Marketing



1997), and their degrees of loyalty may vary or even change. We can model the second (more realistic) scenario using a Markov switching-matrix approach.²

Acquisition and retention. Note that the brand-switching matrix models both the acquisition and the retention of customers. Acquisition is modeled by the flows from other firms to the focal firm, and retention is modeled by the diagonal element associated with the focal firm. The retention probability for a particular customer is the focal firm's diagonal element, as a proportion of the sum of the probabilities in the focal firm's row of the switching matrix. Note that this implies a different retention rate for each customer \times firm combination (we show the details of this in a subsequent section). This describes the acquisition of customers who are already in the market. In growing markets, it is also important to model the acquisition of customers who are new to the market.

The switching matrix and lifetime value. We propose a general approach that uses a Markov switching matrix to model customer retention, defection, and possible return. Markov matrices have been widely used for many years to model brand-switching behavior (e.g., Kalwani and Morrison 1977) and have recently been proposed for modeling customer relationships (Pfeifer and Carraway 2000; Rust, Zeithaml, and Lemon 2000). In such a model, the customer has a probability of being retained by the brand in the subsequent period or purchase occasion. This probability is the retention probability, as is already widely used in CLV models. The Markov matrix includes retention probabilities for all brands and models the customer's probability of switching from any brand to any other brand.³ This is the feature that permits customers to leave and then return, perhaps repeatedly. In general, this "returning" is confused with initial "acquisition" in other customer equity and CLV approaches. The Markov matrix is a generalization of the migration model and is expanded to include the perspective of multiple brands.

To understand how the switching matrix relates to CLV, consider a simplified example. Suppose that a particular customer (whom we call "George") buys once per month, on average, and purchases an average of \$20 per purchase in the product category (with a contribution of \$10). Suppose that George most recently bought from Brand A. Suppose that George's switching matrix is such that 70% of the time he will rebuy Brand A, given that he bought Brand A last time, and 30% of the time he will buy Brand B. Suppose that whenever George last bought Brand B he has a 50% chance of buying Brand A the next time and a 50% chance of buy-

ing Brand B. This is enough information for us to calculate George's lifetime value to both Brand A and Brand B.⁴

Consider George's next purchase. We know that he most recently bought Brand A; thus, the probability of him purchasing Brand A in the next purchase is .7 and the probability of him purchasing Brand B is .3. To obtain the probabilities for George's next purchase, we simply multiply the vector that comprises the probabilities by the switching matrix. The probability of purchasing Brand A becomes $(.7 \times .7) + (.3 \times .5) = .64$, and the probability of purchasing Brand B becomes $(.7 \times .3) + (.3 \times .5) = .36$. We can calculate the probabilities of purchase for Brand A and Brand B as many purchases out as we choose by successive multiplication by the switching matrix. Multiplying this by the contribution per purchase yields George's expected contribution to each brand for each future purchase. Because future purchases are worth less than current ones, we apply a discount factor to the expected contributions. The summation of these across all purchase occasions (to infinity or, more likely, to a finite time horizon) yields George's CLV for each firm. Note that if there are regular relationship maintenance expenditures, they need to be discounted separately and subtracted from the CLV.

The bridge of actionability. We assume that the firm can identify expenditure categories, or drivers (e.g., advertising awareness, service quality, price, loyalty program) that influence consumer decision making and that compete for marketing resources in the firm. We also assume that management wants to trade off the drivers to make decisions about which strategic investments yield the greatest return (Johnson and Gustafsson 2000). The drivers that are projected to yield the highest return receive higher levels of investment. Connecting the drivers to customer perceptions is essential to quantify the effects of marketing actions at the individual customer level. Therefore, it is necessary to have customer ratings (analogous to customer satisfaction ratings) on the brand's perceived performance on each driver. For example, Likert-scale items can be used to measure each competing brand's perceived performance on each driver; perceptions may vary across customers.

The firm may also want to assemble its drivers into broader expenditure categories that reflect higher-level resource allocation. We refer to these as "strategic investment categories." For example, a firm may combine all its brand-equity expenditures into a brand-equity strategic investment category, with the idea that the brand manager is responsible for drivers such as brand image and brand awareness.

²It is also possible to model the share-of-wallet scenario that is common to business-to-business applications by using the concept of fuzzy logic (e.g., Varki, Cooil, and Rust 2000; Wedel and Steenkamp 1989, 1991).

³The Pfeifer and Carraway (2000) Markov model considers only one brand and does not capture brand switching. Its states pertain to recency rather than brand.

⁴Actually, George's CLV also depends on word-of-mouth effects (Anderson 1998; Hogan, Lemon, and Libai 2000), because George may make recommendations to others that increase George's value to the firm. To the extent that positive word of mouth occurs, our CLV estimates will be too low. Similarly, negative word of mouth will make our estimates too high. Although these two effects, being of the opposite sign, tend to cancel out to some extent, there will be some unknown degree of bias due to word of mouth. However, word-of-mouth effects are notoriously difficult to measure on a practical basis.

Modeling the Switching Matrix

Thus, the modeling of CLV requires modeling of the switching matrix for each individual customer. Using individual-level data from a cross-sectional sample of customers, combined with purchase (or purchase intention) data, we model each customer's switching matrix and estimate model parameters that enable the modeling of CLV at the individual customer level.

The utility model. In addition to the individual-specific customer-equity driver ratings, we also include the effect of brand inertia, which has been shown to be a useful predictive factor in multinomial logit choice models (Guadagni and Little 1983). The utility formulation can be conceptualized as

$$(1) \quad \text{Utility} = \text{inertia} + \text{impact of drivers.}$$

To make this more explicit, U_{ijk} is the utility of brand k to individual i , who most recently purchased brand j . The dummy variable LAST_{ijk} is equal to one if $j = k$ and is equal to zero otherwise; \mathbf{X} is a row vector of drivers. We then model

$$(2) \quad U_{ijk} = \beta_{0k}\text{LAST}_{ijk} + \mathbf{X}_{ik}\boldsymbol{\beta}_{1k} + \varepsilon_{ijk},$$

where β_{0k} is a logit regression coefficient corresponding to inertia, $\boldsymbol{\beta}_{1k}$ is a column vector of logit regression coefficients corresponding to the drivers, and ε_{ijk} is a random error term that is assumed to have an extreme value (double exponential) distribution, as is standard in logit models. The β coefficients can be modeled as either homogeneous or heterogeneous.⁵ For the current exposition, we present the homogeneous coefficient version of the model. In a subsequent section, we build and test alternative versions of the model that allow for heterogeneous coefficients. The model can also be estimated separately for different market segments.

The individual-level utilities result in individual-level switching matrices. Essentially, each row of the switching matrix makes a different assumption about the most recent brand purchased, which results in different utilities for each row. That is, the first row assumes that the first brand was bought most recently, the second row assumes that the second brand was bought most recently, and so on. The utilities in the different rows are different because the effect of inertia (and the effect of any variable that only manifests with repeat purchase) is present only in repeat purchases.

Consistent with the multinomial logit model, the probability of choice for individual i is modeled as

$$(3) \quad P_{ijk^*} = \text{Pr}[\text{individual } i \text{ chooses brand } k^*, \text{ given that brand } j \text{ was most recently chosen}] = \exp(U_{ijk^*}) / \sum_k \exp(U_{ijk}).$$

Thus, the individual-level utilities result in individual-level switching matrices, which result in an individual-level CLV.

Brand switching and customer equity. To make the CLV calculation more specific, each customer i has an associated $J \times J$ switching matrix, where J is the number of brands, with switching probabilities p_{ijk} , indicating the probability that customer i will choose brand k in the next purchase, conditional on having purchased brand j in the most recent purchase. The Markov switching matrix is denoted as \mathbf{M}_i , and the $1 \times J$ row vector \mathbf{A}_i has as its elements the probabilities of purchase for customer i 's current transaction. (If longitudinal data are used, the \mathbf{A}_i vector will include a one for the brand next purchased and a zero for the other brands.)

For brand j , d_j represents firm j 's discount rate, f_i is customer i 's average purchase rate per unit time (e.g., three purchases per year), v_{ijt} is customer i 's expected purchase volume in a purchase of brand j in purchase t ,⁶ π_{ijt} is the expected contribution margin per unit of firm j from customer i in purchase t , and \mathbf{B}_{it} is a $1 \times J$ row vector with elements B_{ijt} as the probability that customer i buys brand j in purchase t . The probability that customer i buys brand j in purchase t is calculated by multiplying by the Markov matrix t times:

$$(4) \quad \mathbf{B}_{it} = \mathbf{A}_i \mathbf{M}_i^t.$$

The lifetime value, CLV_{ij} , of customer i to brand j is

$$(5) \quad \text{CLV}_{ij} = \sum_{t=0}^{T_{ij}} (1 + d_j)^{-t f_i v_{ijt}} \pi_{ijt} B_{ijt},$$

where T_{ij} is the number of purchases customer i is expected to make before firm j 's time horizon, H_j (e.g., a typical time horizon ranges from three to five years), and B_{ijt} is a firm-specific element of \mathbf{B}_{it} . Therefore, $T_i = \text{int}[H_j f_i]$, where $\text{int}[\cdot]$ refers to the integer part, and firm j 's customer equity, CE_j , can be estimated as

$$(6) \quad \text{CE}_j = \text{mean}_i(\text{CLV}_{ij}) \times \text{POP},$$

where $\text{mean}_i(\text{CLV}_{ij})$ is the average lifetime value for firm j 's customers i across the sample, and POP is the total number of customers in the market across all brands. Note that the CLV of each individual customer in the sample is calculated separately, before the average is taken.

It is worth pointing out the subtle difference between Equation 5 and most lifetime value expressions, as in direct marketing. Previous lifetime value equations have summed over time period, and the exponent on the discounting factor becomes $-t$. However, in our case, we are dealing with distinct individuals with distinct interpurchase times (or equivalently, purchase frequencies f_i). For this reason, we sum

⁵To the extent that heterogeneity in the regression coefficients exists, the state dependence effect will likely be overestimated (Degeratu 1999; Frank 1962). This would result in underestimation of the effects of the customer equity drivers, which means that the effect of violation of this assumption would be to make the projections of the model more conservative. However, it has been shown that our approach to estimating the inertia effect performs better than other methods that have been proposed (Degeratu 2001).

⁶To simplify the mathematics, we adopt the assumption that a customer's volume per purchase is exogenous. We leave the modeling of volume per purchase as a function of marketing effort as a topic for further research.

over purchase instead of time period.⁷ The exponent $-t/f_i$ reflects that more discounting is appropriate for purchase t if purchasing is infrequent, because purchase t will occur further into the future. If $f_i = 1$ (one purchase per period), it is clear that Equation 5 is equivalent to the standard CLV expression. If $f_i > 1$, the discounting per purchase becomes less than the discounting per period, to an extent that exactly equals the correct discounting per period. For example, for $f_i = 2$, the square root of the period's discounting occurs at each purchase.⁸

We can also use the customer equity framework to derive an overall measure of the company's competitive standing. Market share, historically used as a measure of a company's overall competitive standing, can be misleading because it considers only current sales. A company that has built the foundation for strong future profits is in better competitive position than a company that is sacrificing future profits for current sales, even if the two companies' current market shares are identical. With this in mind, we define *customer equity share* (CES, in Equation 7) as an alternative to market share that takes CLV into account. We calculate customer equity share for each brand j as

$$(7) \quad CES_j = CE_j / \sum_k CE_k.$$

ROI

Effect of changes. Ultimately, a firm wants to know the financial impact that will result from various marketing actions. This knowledge is essential if competing marketing initiatives are to be evaluated on an even footing. A firm may attempt to improve its customer equity by making improvements in the drivers, or it may drill down further to improve subdrivers that influence the drivers (e.g., improving dimensions of ad awareness). This requires the measurement of customer perceptions of the subdrivers about which the firm wanted to know more.

A shift in a driver (e.g., increased ad awareness) produces an estimated shift in utility, which in turn produces an estimated shift in the conditional probabilities of choice (conditional on last brand purchased) and results in a revised Markov switching matrix. In turn, this results in an improved CLV (Equations 4 and 5). Summed across all customers, this results in improved customer equity (Equation 6). We assume an equal shift (e.g., .1 rating points) for all customers, but this assumption can be relaxed if appropriate, because our underlying modeling framework does not require a constant shift across customers.

⁷If standard marketing costs (e.g., retention promotional costs) are spent on a time basis (e.g., every three months), they may either be discounted separately and subtracted from the net present value or be assigned to particular purchases (e.g., if interpurchase time is three months, and a standard mailing goes out every six months, the mailing cost could be subtracted on every other purchase).

⁸We should also note that the expression implies that the first purchase occurs immediately. Other assumptions are also possible.

Projecting financial impact. It is often possible to devote a strategic expenditure to improve a driver, but is that investment likely to be profitable? Modern thinking in finance suggests that improved expenditures should be treated as capital investments and viewed as profitable only if the ROI exceeds the cost of capital. Financial approaches based on this idea are known by such names as "economic value-added" (Ehrbar 1998) or "value-based management" (Copeland, Koller, and Murrin 1996). The increased interest in economic value-added approaches has attracted more attention to ROI approaches in marketing (Fellman 1999).

The discounted expenditure stream is denoted as E , discounted by the cost of capital, and ΔCE is the improvement in customer equity that the expenditures produce. Then, ROI is calculated as

$$(8) \quad ROI = (\Delta CE - E)/E.$$

Operationally, the calculation can be accomplished by using a spreadsheet program or a dedicated software package. Note, though, that even if ΔCE is negative, the ROI expression still holds.

Implementation Issues

Cross-Sectional Versus Longitudinal Data

Our approach requires the collection of cross-sectional survey data; the approach is similar in style and length to that of a customer satisfaction survey. The survey collects customer ratings of each competing brand on each driver. Other necessary customer information can be obtained either from the same survey or from longitudinal panel data, if it is available. The additional information collected about each customer includes the brand purchased most recently, average purchase frequency, and average volume per purchase. The logit model can be calibrated in two ways: (1) by observing the next purchase (from either the panel data or a follow-up survey) or (2) by using purchase intent as a proxy for the probability of each brand being chosen in the next purchase.

Obtaining the Model Input

The implementation of our approach begins with manager interviews and exploratory research to obtain information about the market in which the firm competes and information about the corporate environment in which strategic decisions are made. From interviews with managers, we identified competing firms and customer segments; chose drivers that correspond to current or potential management initiatives; and obtained the size of the market (total number of customers across all brands) and internal financial information, such as the discount rate and relevant time horizon. In addition, we estimated contribution margins for all competitors. If there was a predictable trend in gross margins for any firm in the industry, we also elicited that trend. From exploratory research, using both secondary sources and focus group interviews, we identified additional drivers, which we reviewed with management to ensure that they were managerially actionable items. On the basis of the combined judgment of management and the researchers, we

reduced the set of drivers to a number that allows for a survey of reasonable length. The drivers employed typically vary by industry.

Estimating Shifts in Customer Ratings

The calculation of ROI requires an estimate of the rating shift that will be produced by a particular marketing expenditure. For example, a firm may estimate that an advertising campaign will increase the ad awareness rating by .3 on a five-point scale. These estimates can be obtained in several ways. If historical experience with similar expenditures is available, that experience can be used to approximate the ratings shift. For example, many marketing consulting firms have developed a knowledge base of the effects of marketing programs on measurable indexes. Another way, analogous to the decision calculus approach (Blattberg and Deighton 1996; Little 1970), is to have the manager supply a judgment-based estimate. The manager may reflect uncertainty by supplying an optimistic and a pessimistic estimate. If the outcome was favorable for the optimistic estimate, but unfavorable for the pessimistic estimate, the outcome would be considered sensitive to the rating shift estimate, indicating the need for more information gathering. Another limited cost approach is to use simulated test markets (Clancy, Shulman, and Wolf 1994; Urban et al. 1997) to obtain a preliminary idea of market response. Finally, the marketing expenditure can be implemented on a limited basis, using actual test markets, and the observed rating shift can be monitored (e.g., Rust et al. 1999; Simester et al. 2000).

Calibrating the Data

It is typical in many sampling plans to have respondents with different sampling weights, w_i , correcting for variations in the probability of selection. We can use the sampling weights directly, in the usual way, to generate a sample-based estimate of market share, which we denote as MS_{sample} . If the sample is truly representative, MS_{sample} should be equal to the actual market share, MS_{true} . To make the sample more representative of actual purchase patterns, we can assign a new weight, $w_{i,\text{new}} = (MS_{\text{true}}/MS_{\text{sample}}) \times w_i$ to each respondent, with market shares corresponding to that respondent's most recently chosen brand, which will correct for any sampling bias with respect to any brand. The implied market share from the sample will then equal the actual market share.

If purchase intent rather than actual purchase data is used, the application must be done with some care. Previous researchers have long noted that purchase-intention subjective probabilities occasionally may be systematically biased (Lee, Hu, and Toh 2000; Pessemier et al. 1971; Silk and Urban 1978). We assume that the elicited purchase intentions, p_{ij} , of respondent i purchasing brand j in the next purchase need to be calibrated. In general, we assume that there is a calibrated probability, p^*_{ij} , that captures the true probability of the next purchase. These probabilities can be calibrated in two possible ways. First, if it is possible to follow up with each respondent to check on the next purchase, we can find a multiplier K_j for each brand that best predicts choice. (We set K_j for the first brand arbitrarily to one, without loss of generality, to allow for uniqueness.) The K 's can

be quickly found using a numerical search. If p^*_{ij} is the stated probability of respondent i choosing brand j in the next purchase, the calibrated choice probability is $p^*_{ij} = K_j p_{ij} / \sum_k K_k p_{ik}$. Second, if checking the next purchase is not possible, it is still possible to calibrate the purchase intentions by making an approximating assumption. Assuming that the market share (as the percentage of customers who prefer a brand) for each brand in the near future (including each respondent's next purchase) is roughly constant, we employ a numerical search to find the K_j 's (again setting $K_1 = 1$) for which $MS_{\text{true}} = \text{mean}_i(p^*_{ij})$.

Model Estimation

Principal components regression. In this application, as in customer satisfaction measurement, multicollinearity is an issue that needs to be addressed (Peterson and Wilson 1992). For this reason, we adopt an estimation approach that addresses the multicollinearity issue. Principal components regression (Massy 1965) is an approach that combats multicollinearity reasonably well (Frank and Friedman 1993), yet it can be implemented with standard statistical software. Principal components regression is a two-stage procedure that is widely known and applied in statistics, econometrics, and marketing (e.g., Freund and Wilson 1998; Hocking 1996; Naik, Hagerty, and Tsai 2000; Press 1982). Principal components multinomial logit regression has been used successfully in the marketing literature, leading to greater analysis interpretability and coefficient stability (e.g., Gessner et al. 1988).

The idea is to reduce the dimensionality of the independent variables by extracting fewer principal components that explain a large percentage of the variation in the predictors. The principal components are then used as independent variables in the regression analysis. Because the principal components are orthogonal, there is no multicollinearity issue with respect to their effects. In addition, eliminating the smallest principal components, which may be essentially random, may reduce the noise in the estimation. Because the principal components can be expressed as a linear combination of the independent variables (and vice versa), the coefficients of the independent variables can be estimated as a function of the coefficients of the principal components, and the coefficients (after the least important principal components are discarded) may result in better estimates of the drivers' effects. Estimation details are provided in Appendix A.

Importance of customer equity drivers. The results from the model estimation in Equation 2 provide insight into which customer equity drivers are most critical in the industry in which the firm competes. When examining a specific industry, it is useful to know what the key success factors are in that industry. Ordinarily, this might be explored by calculating market share elasticities for each driver. However, that approach is not correct here, because the drivers are intervally scaled rather than ratio scaled. This means that it is incorrect to calculate percentages of the drivers, as is necessary in the calculation of elasticities. Moreover, our focus is customer equity rather than market share. To arrive at the impact of a driver on customer equity, we need to determine the partial derivative of choice probability, with respect to the driver, for each customer in the sample. That is, if a dri-

ver were improved by a particular amount, what would be the impact on customer choice and, ultimately, on CLV and customer equity? Appendix A provides details of these computations and significance tests for the drivers.

An Example Application

Data and Sampling

Survey items. We illustrate our approach with data collected from customers of five industries. We assume three strategic investment categories: (1) perceived value (Parasuraman 1997; Zeithaml 1988), (2) brand equity (Aaker and Keller 1990), and (3) relationship management (Anderson and Narus 1990; Gummesson 1999). The three categories span all major marketing expenditures (Rust, Zeithaml, and Lemon 2000). We drew heavily on the relevant academic and managerial literature in these areas to build our list of drivers and ensured that the drivers could be translated into actionable expenditures. The resulting survey contained questions pertaining to shopping behavior and customer ratings of each driver for the four or five leading brands in the markets we studied. In addition, several demographics questions were asked at the end of the survey. We selected industries (airlines, electronics stores, facial tissues, grocery, and rental cars) that represented a broad set of consumer goods and services. To save space, we present the details for the airline industry analysis only; however, our approach was similar across the other four industries. The complete list of the survey items used in our analysis of the airline industry appears in Appendix B.

Population. We obtained illustrative data from two communities in the northeastern United States: an affluent small town/suburb and a medium-sized city that adjoins a larger city. Respondents were real consumers who had purchased the product or service in the industry in question during the previous year. Demographic statistics suggest that the sample is representative of similar standard metropolitan statistical areas in the United States, with the exception of generally high levels of education and income. For example, in the small town (with a population of approximately 20,000), the average age of the respondent was 47, the average household had two adults and one child, the average household income was \$91,000, and the average years of education was 17. In the larger city, the average age was somewhat lower (39 years), the average household had two adults and one child, the average household income was \$70,000, and the average years of education was similar to that of the small town.

Sampling. We obtained respondents from three random samples. The first sample, drawn from the city population, answered questions about electronics stores and rental car companies. The second sample, also drawn from the city population, addressed groceries and facial tissues. The third sample, drawn from the small town, focused on airlines. Potential respondents were contacted at random by recruiters from a professional market research organization (by telephone solicitation or building intercept). The screening process consisted of two criteria: (1) the respondent had purchased from the industry in the past 12 months, and (2)

the respondent had a household income of at least \$20,000 per year. Respondents agreed to participate and received \$20 compensation for completing the questionnaire. In the electronics stores and rental cars survey, 246 consumers were approached: 153 were eligible, 144 cooperated, and 7 were disqualified, resulting in a total of 137 total surveys completed. In the groceries and facial tissues survey, 177 consumers were approached: 124 were eligible, 122 cooperated, and 4 were disqualified, resulting in a total of 118 surveys completed. In the airline survey, 229 consumers were approached: 119 were eligible, 105 cooperated, and 5 were disqualified, resulting in a total of 100 surveys completed.

Data collection and preliminary analysis. Data were collected in December 1998 and January 1999 at the firm's offices in each location. The respondents came to the facility to complete the pencil-and-paper questionnaire, which took about 30 minutes. They were then thanked for their participation and compensated. In addition, we obtained aggregate statistics on the small town and city (e.g., percentage of population that uses rental cars, average spent at grocery store) from secondary sources and used them in subsequent analysis. For purposes of financial analysis, we used local population and aggregate usage statistics for predominantly local industries (electronics stores and groceries) and national statistics for predominantly national industries (airlines, facial tissues, and rental cars). Although our random samples may not be fully representative of U.S. users, we extrapolated to the national market for national industries to show the type of dollar magnitudes that can arise given a large population. Because our examples are illustrative, truly precise dollar estimates are unnecessary.

Data were cleaned to eliminate obvious bad cases and extreme outliers. Because listwise deletion of cases would have resulted in too many cases being removed (even though only a relatively small percentage of responses were missing for particular items), we employed mean substitution as our missing data option for all subsequent analyses.⁹ Because we suspected that the relationship drivers would affect primarily repeat purchasers, we collected relationship items only for the brand most recently purchased.¹⁰ We mean-centered the relationship-related drivers for the cases in which the brand considered was the previously purchased brand, and we set them equal to zero for the cases in which the brand considered was different from the previously purchased brand. This enabled the "pure" inertia effect to be separated from the relationship effect of the drivers.

Choice Model Results

Principal components analysis results. We reduced the dimensionality of the predictor variables in each industry by conducting a principal components analysis. We used an eigenvalue cutoff of .5, which we judged to provide the best

⁹Mean substitution can result in biased estimates, but in our judgment, the additional effort of employing a more sophisticated missing values procedure (e.g., data imputation) was not justified in this case, given the relatively low percentage of missing values.

¹⁰This decision was based solely on the researchers' best judgment. Our model does not require this.

trade-off between parsimony and managerial usefulness.¹¹ The airline analysis began with 17 independent variables, and we retained 11 orthogonal factors. Table 2 shows the loadings on the rotated factors. The resulting factor structure is rich. All the factors are easily interpretable. The few negative loadings are small and insignificant; they are zero for all practical purposes. All drivers load on only one factor, and many (e.g., inertia, quality, price, convenience, trust, corporate citizenship) load on their own unique factor.

There is some degree of discrimination among the value, brand, and relationship strategic investment categories in that drivers in the three strategic action categories of different drivers do not correlate highly on the same factors. As we expected, the strategic investment categories, value, brand, and relationship are not unidimensional. The drivers that constitute the categories can be grouped for managerial purposes as managers consider them, but drivers in a particular strategic investment category may be quite distinct in the customer's mind.

Logit regression results. Using the resulting factors as independent variables, we conducted multinomial logit analyses, using the analysis we described previously. Table 3 shows the coefficients that arise from the multinomial logit regression analysis, highlighting the significant factors. Using Equations A1–A9, we converted the factor-level results to the individual drivers. The resulting coefficients, standard errors, and test statistics are shown in Table 4. All

¹¹The 1.0 eigenvalue cutoff (Kaiser 1960) is typically employed in marketing, but it is just one of many possible cutoff criteria (for two alternatives, see Cattell 1966; Jolliffe 1972). As Kaiser (1960, p. 143), who proposed the 1.0 cutoff, points out, “by far [the] most important viewpoint for choosing the number of factors [is] ... psychological meaningfulness.” In other words, the cutoff should be chosen such that the results are substantively meaningful, which is our justification for using the particular cutoff level that we chose.

the drivers are significant and have the correct sign, but some drivers have a larger effect than others. The most important drivers span all three strategic investment categories. In addition to the drivers, inertia has a large, significant impact (.849, $p < .01$). Among the value-related drivers, convenience has the largest coefficient (.609), followed by quality (.441); for brand-related drivers, direct mail information has the largest impact (.638), followed by ad awareness (.421) and ethical standards (.421). The loyalty program (.295) and preferential treatment (.280) are the most important relationship-related drivers.

Model Testing and Validation

We tested and validated the core choice model in several different ways. We tested for brand-specific effects, heterogeneity of response, a more general covariance matrix, and the reliability of the coefficient estimates.

Brand-specific effects. The model in Equation 2 assumes that there are no brand-specific effects. We tested the validity of this assumption by including brand-specific constants in the model of Equation 2. Testing the significance of the more complicated model can be accomplished through the use of a nested-likelihood-ratio chi-square test (in the airline application, this involves three degrees of freedom, reflecting a number of brand-specific constants that is equal to the number of brands minus one). The resulting nested model comparison was not significant ($\chi^2_3 = .977$), from which we conclude that brand-specific constants are not required.¹²

Heterogeneity of response. It is reasonable to suspect that there may be unobserved heterogeneity of response

¹²This nested chi-square was also insignificant in the other four industries that we studied (electronics = 6.79, facial tissues = 1.00, grocery = 5.82, and rental cars = .28).

TABLE 2
Factor Loadings: Airline Industry

Driver	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
Inertia	-.013	-.004	.033	.038	.015	.116	-.024	.984	.029	.043	.002
Quality	.097	.058	.174	.076	.147	.212	.014	.049	.068	.904	.083
Price	.044	-.007	.128	.054	.078	.023	.039	.030	.975	.059	.034
Convenience	.078	.068	.219	.161	.043	.830	.066	.163	.018	.260	-.015
Ad awareness	-.031	.130	.038	.938	-.010	.022	.048	-.011	.074	.101	.058
Information	.216	-.077	.248	.656	.322	.299	-.207	.125	-.038	-.058	.016
Corporate citizenship	.011	.122	.150	.093	.880	.001	.256	.021	.077	.137	.006
Community events	.021	.100	.188	-.042	.226	.051	.921	-.026	.041	.011	.029
Ethical standards	-.016	.044	.605	.105	.458	.266	.028	-.034	.104	.109	.218
Image fits my personality	.098	.112	.878	.107	.069	.092	.203	.058	.110	.142	.081
Investment in loyalty program	.921	.044	.090	.032	-.007	-.060	.018	.014	-.003	.137	-.103
Preferential treatment	.898	.087	.082	-.002	.022	-.071	-.029	.032	-.007	.077	.104
Know airline's procedures	.708	.232	-.022	.116	.029	.166	.058	-.033	.010	-.069	.240
Airline knows me	.681	.309	-.073	-.059	-.001	.356	-.012	-.061	.136	-.075	.219
Recognizes me as special	.214	.851	.069	.077	-.036	.042	.138	-.004	-.044	.118	.092
Community	.175	.876	.065	.031	.166	.035	-.015	.001	.036	-.042	.129
Trust	.246	.227	.179	.069	.041	-.003	.031	.006	.038	.091	.889

Notes: Loadings greater than .5 are shown in bold.

TABLE 3
Logit Regression Results: Airline Industry

Independent Variable	Coefficient	Standard Error	b/s.e.	p
F1	.325**	.122	2.65	.008
F2	-.031	.118	-.26	.795
F3	.421*	.210	2.00	.045
F4	.459	.285	1.61	.107
F5	.212	.228	.93	.352
F6	.331*	.159	2.08	.037
F7	-.081	.279	-.29	.771
F8	.633**	.100	6.36	.000
F9	.034	.164	.21	.835
F10	.184	.147	1.26	.209
F11	-.033	.115	-.29	.772
Log-likelihood	= -98.46			
Chi-square (11 degrees of freedom)	= 69.246**			

* $p < .05$.

** $p < .01$.

TABLE 4
Driver Coefficients: Airline Industry

Driver	Coefficient	Standard Error	b/s.e.
Inertia	.849	.075	11.341*
Quality	.441	.041	10.871*
Price	.199	.020	9.858*
Convenience	.609	.093	6.553*
Ad awareness	.421	.099	4.242*
Information	.638	.082	7.819*
Corporate citizenship	.340	.045	7.617*
Community events	.170	.024	6.974*
Ethical standards	.421	.053	7.901*
Image fits my personality	.390	.050	7.874*
Investment in loyalty program	.295	.027	10.956*
Preferential treatment	.280	.026	10.857*
Know airline's procedures	.238	.027	8.779*
Airline knows me	.249	.041	6.108*
Recognizes me as special	.167	.017	9.771*
Community	.151	.016	9.412*
Trust	.203	.023	8.725*

* $p < .01$.

across the respondents. That is, expressed in terms of Equation 2, the β s may be different across respondents. To test this, we employed a random coefficients logit model (Chintagunta, Jain, and Vilcassim 1991) in which we permitted the driver coefficients to be distributed as an independent multivariate normal distribution. The log-likelihood improved from -97.58 to -93.24, which is an insignificant improvement ($\chi^2_{11} = .8.68$). Therefore, we conclude that the random coefficients logit formulation does not produce a better model and that it is not worthwhile in this case to model unobserved heterogeneity in the parameters.

Correlated errors. Another way the independence from irrelevant alternatives property can be violated is if the error terms in Equation 2 are correlated. For example, it is possible that people who prefer American Airlines more than the model predicted will systematically dislike Southwest Airlines more than the model predicted. To address this issue, we turned to a multinomial probit model (Chintagunta 1992). In this model, the error terms in Equation 2 are assumed to be normally distributed rather than extreme value, and they are permitted to have a general covariance matrix.

Our original logit model is no longer a constrained version of the more complicated model, so we cannot do the nested likelihood-ratio chi-square test. However, by comparing the general multinomial probit model with a multinomial probit model in which the error terms are assumed to be independent, we can address the issue of whether modeling the more general covariance matrix is useful. This results in a nested test. We found that the uncorrelated errors version of the model resulted in a log-likelihood of -98.46 (slightly worse than the multinomial logit log-likelihood) and that the more general model produced a log-likelihood of -97.57 . The improvement is insignificant ($\chi^2_3 = .82$). We also can compare the general multinomial probit model with the original multinomial logit model by using the Akaike information criterion. The improvement from -97.58 to -97.57 does not compensate for the additional three estimated parameters (we would need a log-likelihood improvement of at least 3.0), suggesting that the general multinomial probit model is not better than our multinomial logit model. Thus, we conclude that the more general covariance matrix is not warranted.

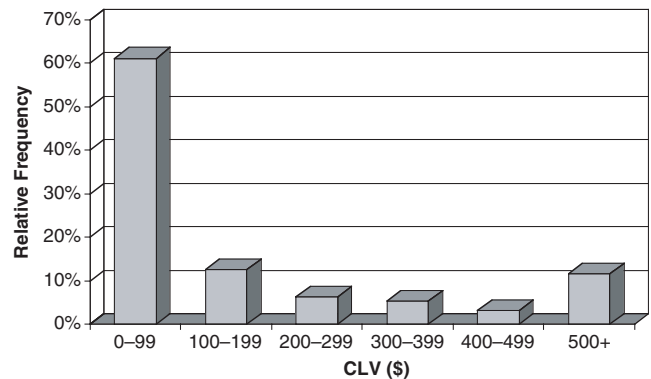
Coefficient reliability. Given our relatively small sample size (96 usable data points after the data are cleaned), we were unable to pursue split-half tests or complete holdout samples. However, to further understand the reliability of our model estimates, we randomly split our sample into three parts (A, B, and C) and estimated our model on AB, AC, and BC. The mean range (and median range) of the coefficient estimates across the 11 factors was .14; that is, on average, the swing between the largest and smallest coefficient estimate across the three samples was .14, which comes out to about .6 standard errors, on average. Thus, the model appears to produce reasonably stable coefficient estimates.

CLV

Using Equation 5, we calculated CLV for American Airlines for each respondent in our airline sample. To operationalize the equation, we assumed a time horizon of three years, a discount rate of 10%, and a contribution margin of 15%. The 15% figure was approximately equal to the average operating margin for the industry for the five years preceding the survey, according to annual reports of the four firms we studied (since our study, airline industry operating margins have declined). We also based our contribution margin figures in the other four industries on financial data from annual reports. To extend the CLV figures to the firm's U.S. customer equity, we used U.S. Census data to determine the number of adults in the United States (187,747,000), and we then combined this with the percentage of U.S. adults who were active users of airline travel (23.3%), yielding a total number of U.S. adult airline customers of 43,745,051. To approximate the total customer equity, we multiplied this number by the average CLV across our respondents. Note that though we used average CLV to project customer equity, we calculated CLV at the individual customer level for each customer in the sample.

Customer loyalty and CLV. Some insights can be obtained from examining American Airlines' CLV distribu-

FIGURE 2
Distribution of CLV: American Airlines



tion. For example, Figure 2 shows the distribution of CLV across American Airlines' customers. The \$0-\$99 category includes more than 60% of American's customers, and the \$500-plus category includes only 11.6% of customers, indicating that the bulk of American's customers have low CLV. Figure 3 also indicates that American's customers are fickle. Almost half of American's customers have a 20% or less share-of-wallet (by CLV) allocated to American. Only 10.5% give more than 80% of their CLV to American. This percentage shows dramatically that the vast majority of American's customers cannot be considered monogamously loyal. Figure 4 shows a startling picture of the percentage of American's customer equity that is contributed by each CLV category. The \$0-\$99 category, though by far the largest (more than 60% of American's customers), produces less than 10% of American's customer equity. In contrast, the \$500-plus CLV category, though only 11.6% of American's customers, produces approximately 50% of American's customer equity.

Comparison with the lost-for-good CLV model. Previously, we proposed that some models of CLV that do not account for customers' returning systematically underesti-

FIGURE 3
Distribution of CLV Share (Share of Wallet): American Airlines

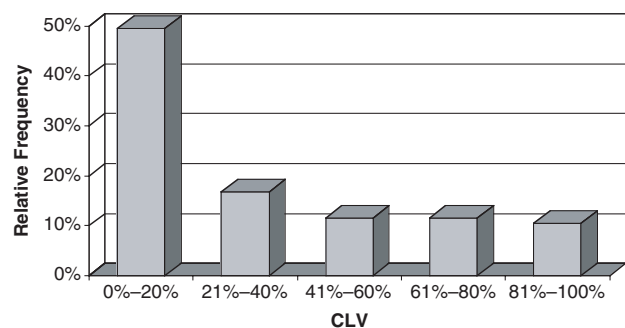
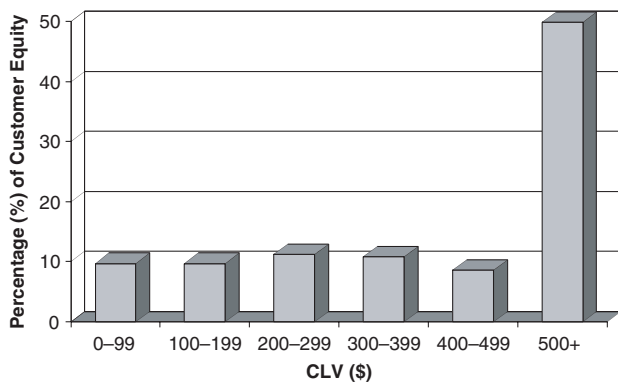


FIGURE 4
Percentage Customer Equity by CLV Category:
American Airlines



mate CLV and customer equity (for an exception, see Dwyer 1997). Using the airline sample, we explored the degree to which this was true. The lost-for-good model is simply a constrained version of our switching model, such that all probabilities of switching from another brand to the focal brand are zero. In other words, to calculate the results, we considered only the customers who were retained from the first purchase. When the customer chose another brand, we gave a probability of zero to any further purchase from the focal brand. For American Airlines, our brand-switching model gives a customer equity of \$7.303 billion. Without accounting for switching back, the estimated customer equity declines to \$3.849 billion. Thus, the lost-for-good model provides a systematic underestimation of customer equity that, in this case, is an underestimation of 47.3%.

Customer equity and the value of the firm. It has been suggested (Gupta, Lehmann, and Stuart 2001) that customer equity is a reasonable proxy for the value of the firm. Our analysis of American Airlines provides some support for this

idea. Multiplication of American's average CLV (\$166.94) by the number of U.S. airline passengers (43,745,051) yields a total customer equity for American of \$7.3 billion. Given American's opening share price for 1999 (\$60) and its number of shares outstanding at that time (161,300,000) (AMR Corporation 1999), we calculate a market capitalization of \$9.7 billion. Because our projection ignores profits from international customers and nonflight sources of income, our customer equity calculation is largely compatible with American's market capitalization at the time of the survey.

Projected Financial Return

Our framework enables the financial impact of improvement efforts to be analyzed for any of the usual marketing expenditures. For example, American Airlines recently spent a reported \$70 million to upgrade the quality of its passenger compartments in coach class by adding more leg room. Is such an investment justified? To perform an analysis such as this, we estimated the amount of ratings shift and the costs incurred in effecting the ratings shift. We then used the ratings shift to alter (for each respondent) the focal brand's utility, switching matrix, and CLV (see Equations 2-5), which, when averaged across respondents and projected to the size of the population (see Equation 6), resulted in a revised estimate for the firm's customer equity. In this way, and using the discount rate and contribution margin we discussed previously, we analyzed the recent American Airlines seating improvement. We used the \$70 million cost figure reported by the company.

If we assume that the average for the item that measures quality of the passenger compartment (a subdriver of quality) increases by .2 rating points on the five-point scale, our analysis (see Table 5) indicates that customer equity will improve by 1.39%, resulting in an improvement in customer equity of \$101.3 million nationally, or an ROI of 44.7%, which indicates that the program has the potential to be a large success. Table 5 shows the results of similar analyses from the other four industries. For example, a \$45 million expenditure by Puffs facial tissues to improve ad awareness

TABLE 5
Projected ROI from Marketing Expenditures

Company (Industry)	Area of Expenditure	Geographic Region	Investment	Amount Improved	Percentage Improvement in Customer Equity	Dollar Improvement in Customer Equity	Projected ROI
American (airlines)	Passenger compartment	United States	\$70 million	.2 rating point	1.39%	\$101.3 million	44.7%
Puffs (facial tissues)	Advertising	United States	\$45 million	.3 rating point	7.04%	\$58.1 million	29.1%
Delta (airlines)	Corporate ethics	United States	\$50 million	.1 rating point	1.68%	\$85.5 million	71.0%
Bread & Circus (groceries)	Loyalty programs	Local market	\$100,000	.5 rating point in two measures	7.04%	\$87,540	-12.5%

by .3 rating points would result in a \$58.1 million improvement in customer equity and an ROI of 29.1%.¹³

It is even possible to measure the financial impact of corporate ethical standards or corporate citizenship. For example, if Delta spent \$50 million to improve customers' perceptions of Delta's ethical standards by .1 rating points, this would project to a customer equity improvement of \$85.5 million (a 1.68% increase). Such findings may cause some airlines to reconsider practices such as canceling flights that are not full in order to be profitable.

Not all investments will project to be profitable. For example, suppose that the grocery store Bread & Circus decides to spend \$100,000 in the local retail area to improve its loyalty program ratings across two measures by .5 points. The projected benefit is not enough to justify the expenditure, and the ROI is -12.5%.

The preceding examples illustrate only some of the marketing expenditures that can be evaluated by means of the customer equity framework. Any marketing expenditure can be related to the drivers of customer equity, measured, and evaluated financially. This capability enables a firm to screen improvement ideas either before application or after a test market has nailed down the expected degree of improvement.

Model Sensitivity

The preceding analyses are based on point estimates, but how sensitive is the ROI model to errors of estimation or measurement? Sensitivity to errors of estimation can be analyzed by considering the sampling distribution of β_x . Appendix A shows how to construct confidence intervals for β_x . Then, by applying the end points of the confidence interval to the ROI model, it is possible to analyze the sensitivity of ROI to estimation error. In general, this error is of more concern on the low side, because overoptimism may result in inappropriate expenditures. With this in mind, we suggest calculation of a coefficient, $\beta_{\bar{x}}$, which will be greater than the true value only 5% of the time. Assuming that there is a large n , this is calculated as

$$(9) \quad \beta_{\bar{x}} = \beta_x - 1.645(\text{standard error of } \beta_x).$$

Then, $\beta_{\bar{x}}$ can be used to produce "conservative" projections of the customer equity change and the ROI. This can be done by inserting $\beta_{\bar{x}}$ directly into the customer equity calculations. For example, if we calculate a conservative estimate of customer equity impact for the American Airlines example in Table 5, we obtain a \$93.9 million increase in customer equity, or a 1.29% increase. This would result in a 34.2% ROI, indicating that even a conservative estimate shows a quite favorable return.

Sensitivity to errors of measurement can be addressed by considering the sampling distribution of the sample mean. In Equation A5 in Appendix A, unlike the case in regression analysis, the level of a variable affects the extent to which a change in the variable affects choice and thus utility, CLV, and customer equity. By evaluating the end points of the

confidence interval for the sample mean of a variable to be improved, we can thus obtain a confidence interval for the ROI that will result from a shift in that variable. We performed this analysis for the Delta Airlines corporate ethics example in Table 5. A 95% confidence interval for the mean on the corporate ethics variable was $3.346 \pm .188$, which results in a 95% confidence interval for corporate ethics improvement of \$83.1 million/\$87.8 million and a 95% confidence interval for ROI of 66%/76%.

If the projected rating shift results from a test market, the sampling distribution of the rating shift can also be employed to generate a confidence interval. Under the assumption that the sources of error are independent, which is not unreasonable, it would then be straightforward to simulate an all-inclusive confidence interval for ROI, incorporating errors in the model coefficient estimate, estimated sample mean, and estimated shift that are based on an assumption of a multivariate normal distribution with orthogonal components.

Discussion and Conclusions

Contributions to Theory and Practice

We make several contributions to marketing theory and practice. First, we identify the important problem of making all of marketing financially accountable, and we build the first broad framework that attempts to address the problem. We provide a unified framework for analyzing the impact of competing marketing expenditures and for projecting the ROI that will result from the expenditures. This big-picture contribution extends the scope of ROI models in marketing, which to date have focused on the financial impact of particular classes of expenditure and have not addressed the general problem of comparing the impact of any set of competing marketing expenditures. Our work is the first serious attempt to address this issue in its broadest form: the trading off of any strategic marketing alternatives on the basis of customer equity. Marketing Science Institute member companies have identified this research area as the most important problem they face today.

Second, we provide a new model of CLV, incorporating the impact of competitors' offerings and brand switching; previous CLV models have ignored competition. We also discount according to purchase rather than time period. Previous CLV models have been limited to the consideration of purchases made in prespecified time units, which is realistic for some businesses (e.g., subscription services, sports season tickets) but not for others (e.g., consumer packaged goods). By discounting according to purchase, at the individual level, our model is more widely applicable. The approach set out previously considers customer equity for the entire relevant competitive set, which has two advantages over existing approaches. First, this approach considers the expected lifetime value of both existing customers and prospective customers, thereby incorporating acquisition and retention (for the focal firm and competitors) in the same model. Second, by explicitly considering competitive effects in the choice decision, it is possible to use the model

¹³To conserve space, we show the details only for the airline example, but the details of the other industry examples are similar.

to consider the impact of competitive responses on the firm's customer equity.

Third, we provide a method for estimating the effects of individual customer equity drivers, testing their statistical significance, and projecting the ROI that will occur from expenditures on those drivers. We present a principal components multinomial logit regression model for estimating the Markov brand-switching matrix, and we separate the driver effects from the inertia effect. The identification and measurement of key drivers has been a process widely and successfully employed in the fields of customer satisfaction measurement and customer value management (e.g., Gale 1994; Kordupleski, Rust, and Zahorik 1993). We extend this idea to customer equity. By doing so, companies can answer questions such as, "Should we spend more on advertising, or should we improve service quality" and "Which will have a bigger effect"?

Fourth, customer equity provides a theoretical framework for making the firm truly customer centered, and it is applicable to a wide variety of market contexts and industries. Basing strategic investment on the drivers of customer equity is an outside-in approach that directly operationalizes these fundamental marketing concepts. In other words, the customer equity approach provides a means of making strategic marketing decisions inherently information driven, which is consistent with the long-term trends of decreasing costs for information gathering and information processing.

Fifth, application of the customer equity framework is consistent with practical management needs. The results provide insight into competitive strengths and weaknesses and an understanding of what is important to the customer. By contrasting the firm's customer equity, customer equity share, and driver performance with those of its competitors, the firm can quickly determine where it is gaining or losing competitive ground with respect to the value of its customer base. In addition, the model results include the distribution of CLV across the firm's customers, the distribution of CLV share (discounted share-of-wallet) across the firm's customers, and the percentage of the firm's customer equity provided by the firm's top X% of customers. Collectively, the information gives useful information about how to segment the firm's customers on the basis of importance. Finally, the mathematical infrastructure of our framework can be implemented by means of widely available statistical packages and spreadsheet programs, and we have conducted all the analyses by using only standard, commercially available software packages.

Limitations and Directions for Further Research

In this article, we have developed and illustrated a practical framework for basing marketing strategy on CLV and customer equity. As with any new endeavor, there is much work yet to be done. Specifically, we have determined seven key areas for further research. First, the effects of market dynamics on customer equity should be examined. For example, if the market is rapidly expanding or rapidly shrinking, an assumption of stable market size is inappropriate. In such markets, it would be necessary to model the changing size of the market and relate that to customer

equity. This also implies the explicit modeling of a birth and death process for customers in the market. New-to-the-world products and services and markets in which firms are expanding globally are examples of contexts in which we believe this will be particularly important.

Second, our model assumes that there is one brand or product in the firm and does not consider cross-selling between a firm's brands or products. We believe that the model we have described provides a solid foundation for firms to understand what drives customer equity in a given brand or product category. However, because many firms have multiple offerings and hope to encourage customer cross-buying of these products, it will be important to understand the influence of the drivers of customer equity on customer cross-buying behavior and to incorporate the impact of cross-selling on customer equity. This is particularly important for firms that rely on customer cross-buying behavior for long-term customer profitability (e.g., financial service firms).

Third, we adopt the assumption that a customer's volume per purchase is exogenous. An extension of this research would permit volume per purchase to vary as a function of marketing effort. For example, it will be important to understand whether marketing efforts that may result in forward buying (e.g., short-term price discounts) have a long-term effect on customer equity.

Fourth, there is a need to develop dynamic models of CLV and customer equity. Traditional models of CLV have been adopted from the net-present-value approach in the finance literature. Understanding how the value of the firm's customers (and overall customer equity) changes over time will enable managers to make even better marketing investments. There is also an opportunity to develop richer models of CLV that incorporate a deeper understanding of consumer behavior.

Fifth, there is an opportunity to relate customer equity to corporate valuation (Gupta, Lehmann, and Stuart 2001). This should involve the evaluation of corporate assets, liabilities, and risk, as well as the estimated customer equity. Sixth, applications of this framework and further empirical validation of its elements would be useful, especially across different cultures. For example, in what kinds of cultures are various drivers more important or less important, and why? Seventh, although our model incorporates competition, it makes no provision for competitive reactions. An extension of this work might involve a game theoretic competitive structure in order to understand the effects of potential competitive reactions to the firm's intended improvements in key drivers of customer equity.

Summary

We have provided the first broad framework for evaluating return on marketing. This enables us to make marketing financially accountable and to trade off competing strategic marketing investments on the basis of financial return. We build our customer equity projections from a new model of CLV, one that permits the modeling of competitive effects and brand-switching patterns. Customer equity provides an information-based, customer-driven, competitor-cognizant,

and financially accountable strategic approach to maximizing the firm's long-term profitability.

Appendix A Estimation Details

Principal Components Regression

The independent variables for the principal components analysis are all the drivers and the LAST variable. The vector \mathbf{X}_{ijk} denotes the original independent variables for each customer i by previously purchased firm j by next-purchase firm k combination. Treating the customer by firm combinations as replications, we extract the largest principal components of \mathbf{X}_{ijk} and rotate them using varimax rotation to maximize the extent to which the factors load uniquely on the original independent variables, thereby aiding managerial interpretability. The vector \mathbf{F}_{ijk} denotes the rotated factor. These form the independent variables for our logit regression, which we describe subsequently.

Expressing Equation 2 in terms of the underlying factors leads to the following:

$$(A1) \quad U_{ijk} = \mathbf{F}_{ijk}\boldsymbol{\gamma} + \varepsilon_i,$$

where $\boldsymbol{\gamma}$ is a vector of coefficients.

From factor analysis theory, it is known that the factors are linear combinations of the underlying variables \mathbf{X}_{ijk} . In other words, there exists a matrix \mathbf{A} for which $\mathbf{F}_{ijk} = \mathbf{X}_{ijk}\mathbf{A}$. However, the idea of the principal components analysis was to discard the potentially muddling effects of the least important components. Denoting \mathbf{A}^* as the subvector of \mathbf{A} that corresponds to the reduced factor space (discarding the principal components that do not meet the eigenvalue cutoff) and $\boldsymbol{\gamma}^*$ as the estimated $\boldsymbol{\gamma}$ that corresponds to the reduced space, Equation A1 can be expressed as

$$(A2) \quad \hat{U}_{ijk} = (\mathbf{X}_{ijk}\mathbf{A}^*)\boldsymbol{\gamma}^* = \mathbf{X}_{ijk}(\mathbf{A}^*\boldsymbol{\gamma}^*),$$

where \hat{U}_{ijk} is the estimated utility, which means that $\boldsymbol{\beta}^* = \mathbf{A}^*\boldsymbol{\gamma}^*$ can be the estimated coefficient vector. In other words, the coefficients of \mathbf{X}_{ijk} are obtained by multiplying the regression coefficients obtained from the logit regression on the factors by the factor coefficients that relate the drivers to the factors.

Logit Estimation

Usually in multinomial logit regression, the observed dependent variable values are ones and zeroes, corresponding to the purchased brand (1 = "brand was purchased," 0 = "brand was not purchased"). This will be the case if the next purchase is observed from a longitudinal panel or follow-up survey. However, if purchase intent is used as a proxy for next purchase, the dependent variable values will be proportions that correspond to the stated (or calibrated) purchase intention probabilities. This does not create any difficulties. From Equation 9, we have $U_{ijk} = \mathbf{F}_{ijk}\boldsymbol{\gamma}^* + \varepsilon_i$, after discarding the principal components that did not meet the cutoff. Using the laws of conditional probability, we can express the likelihood of a particular parameter vector $\boldsymbol{\gamma}^*$ given respondent i 's observed next purchase (or purchase intention) vector \mathbf{p}^*_i as

$$(A3) \quad L(\boldsymbol{\gamma}^*|\mathbf{p}^*_i) = \sum_{j=1}^J L(\boldsymbol{\gamma}^*|Y_{ij} = 1)P(Y_{ij} = 1) \\ = \sum_{j=1}^J L(\boldsymbol{\gamma}^*|Y_{ij} = 1)p^*_{ij},$$

where Y_{ij} equals one if customer i chooses brand j and equals zero otherwise, the likelihoods on the right side are the usual 0–1 logit likelihood expressions obtained as in Equation 3, and p^*_{ij} is the element of \mathbf{p}^*_i that corresponds to firm j . The resulting likelihood for the sample is then the product of the individual likelihoods across the respondents. It is easily shown that with this adjustment in the likelihood, the standard logit regression maximum likelihood algorithms can be employed (Greene 1997, p. 916, 1998, pp. 520, 524). The same adjustment of the likelihood does not affect the derivation of the asymptotic distribution of the regression coefficients¹⁴ (as is evident in McFadden's [1974, pp. 135–38] work), which means that the usual chi-square statistics, as given in standard logit software such as LIMDEP, can still be employed, even if the \mathbf{p}^*_{ij} vector is not all zeroes and ones.

From Equation 3, it is easily shown that the partial derivative of probability of choice with respect to utility, for respondent i and firm k , is¹⁵

$$(A4) \quad D_{ik} = \partial P_{ik} / \partial U_{ik} \\ = \left\{ \left[\sum_{k^*} \exp(U_{ik^*}) \right] \left[\exp(U_{ik}) \right] \right. \\ \left. - \left[\exp(U_{ik}) \right]^2 \right\} / \left[\sum_{k^*} \exp(U_{ik^*}) \right]^2 \\ = \left[\exp(U_{ik}) \right] / \left[\sum_{k^*} \exp(U_{ik^*}) \right] \\ \times \left[\sum_{j \neq k} \exp(U_{ij}) / \sum_{k^*} \exp(U_{ik^*}) \right] \\ = p^*_{ik} \left\{ \left[\sum_j \exp(U_{ij}) - \exp(U_{ik}) \right] / \right. \\ \left. \left[\sum_{k^*} \exp(U_{ik^*}) \right] \right\} \\ = p^*_{ik}(1 - p^*_{ik}).$$

Then, from Equation A2 we have

$$(A5) \quad \partial P_{ik} / \partial \mathbf{X}_{ijk} = \partial P_{ik} / \partial U_{ik} \times \partial U_{ik} / \partial \mathbf{X}_{ijk} = (\mathbf{A}^*\boldsymbol{\gamma}^*)D_{ik} \\ = (\mathbf{A}^*\boldsymbol{\gamma}^*) p^*_{ik}(1 - p^*_{ik}).$$

This equation shows how each customer's brand-switching matrix will change given a change in any driver (or changes in more than one driver). This result is nonlin-

¹⁴Actually, convergence is faster, because the probabilities of next purchase are given directly, so the law of large numbers does not need to be evoked with respect to the dependent variable.

¹⁵For convenience, we suppress the j subscript for D , P , and U , because for any customer i in the sample, j is fixed.

ear and implies diminishing returns for any driver improvement. By applying the altered switching matrix in Equation 4, reestimating CLV by using Equation 5, and aggregating across customers by using Equation 6, we find the impact on customer equity.

The relative importance of each driver, measured as the impact of a marginal improvement in the driver on utility, can also be addressed as a proportion of the total marginal impact summed across all drivers. In other words, the importance of driver x is the per-unit amount that it contributes to utility, and the relative importance is that amount expressed as a percentage.

$$(A6) \quad \text{Importance} = \sum_{c=1}^C (A_{cx} \gamma_c), \text{ and}$$

$$(A7) \quad \text{Relative importance} = \left[\frac{\sum_{c=1}^C (A_{cx} \gamma_c)}{\sum_{x^* \in S_d} \sum_{c=1}^C (A_{cx^*} \gamma_c)} \right] \times 100,$$

where C is the set of retained principal components, A_{cx} is the factor coefficient relating driver x to factor c , and γ_c is the logit coefficient corresponding to factor c .

In addition, we address the statistical significance of the drivers. The coefficients, γ_c , as estimated by the logit model, are distributed asymptotically normally, and mean and variance are estimated and reported by standard logit regression software. If the estimated logit coefficient and variance of the estimate for factor c are $\hat{\gamma}_c$ and $\hat{\sigma}_c^2$, respectively, and $\beta_x = \sum_c A_{cx} \gamma_c$ is the coefficient estimator for driver x , then, if we assume that the $\hat{\gamma}_c$'s are distributed independently, β_x is a linear combination of independent normal distributions and thus is also normally distributed. Specifically:

$$(A8) \quad \text{Standard error of } \beta_x = \left(\sum_c A_{cx}^2 \hat{\sigma}_c^2 \right)^{\frac{1}{2}},$$

which results asymptotically in the following z-test for β_x :

$$(A9) \quad z = \beta_x / \left(\sum_c A_{cx}^2 \hat{\sigma}_c^2 \right)^{\frac{1}{2}},$$

which is easily calculated from the results of the principal components analysis (for A_{cx}^2) and logit analysis (for β_x and $\hat{\sigma}_c^2$).

Computational Issues in Estimating CLV

If the time horizon is long or the customer's frequency of purchase is high, there may be many purchases expected before the time horizon, which increases computation considerably. Therefore, it is useful to make a simplifying approximation that can speed up the computation. In practice, the expected purchase probabilities, B_{ijt} , approach equilibrium and change little after about 15 purchases. This enables us to employ the approximation that the purchase probabilities do not change after 15 purchases. If $T_i \leq 15$, we can estimate CLV_{ij} as in Equation 5. However, if $T_i > 15$, we

can simplify the calculations. Let $CLV_{ij}(15)$ denote the lifetime value of customer i to firm j in 15 purchases, as calculated by Equation 5, and let $CLV_{ij}^*(T_i)$ and $CLV_{ij}^*(15)$ denote the lifetime values that would occur (through T_i purchases and 15 purchases, respectively) if the purchase probabilities were constant and equal to $B_{ij,15}$.¹⁶ The expected lifetime value of the purchases beyond purchase 15 can be approximated as $CLV_{ij}^*(T_i) - CLV_{ij}^*(15)$. This is helpful because CLV^* can be viewed as a net present value of an annuity, and it can be calculated in closed form because the probabilities $B_{ij,15}$ are constant. Expressing the individual-specific discount rate per purchase as $d_i^* = d_i^{-1/f_i}$, we have the standard expression for the net present value of an annuity:

$$(A10) \quad CLV_{ij}^*(t) = v_{ij} \pi_{ijt} B_{ij,15} (1/d_i^*) [1 - (1 + d_i^*)^{-t}],$$

from which we obtain the estimated lifetime value of

$$(A11) \quad \text{Estimated } CLV_{ij} = CLV_{ij}(15) + CLV_{ij}^*(T_i) - CLV_{ij}^*(15).$$

Appendix B Example Survey Items (Airline Survey)

Here are some examples of survey items that might be used to measure customer equity and its drivers. These items are from the survey that we used to analyze the airline market. (The headings in this Appendix are for explanatory purposes and would not be read to the respondent.)

Market Share and Transition Probabilities

1. Which of the following airlines did you most recently fly? (please check one)
2. The next time you fly a commercial airline, what is the probability that you will fly each of these airlines? *Probability (please provide a percentage for each airline, and have the percentages add up to 100%)*

Size and Frequency of Purchase

3. When you fly, how much on average does the airline ticket cost?
 - _____ less than \$300
 - _____ between \$300 and \$599
 - _____ between \$600 and \$899
 - _____ between \$900 and \$1199
 - _____ between \$1200 and \$1499
 - _____ between \$1500 and \$1799
 - _____ between \$1800 and \$2099
 - _____ \$2100 or more
4. On average, how often do you fly on a commercial airline?
 - _____ once a week or more
 - _____ once every two weeks
 - _____ once a month
 - _____ 3–4 times per year

¹⁶We could also use the equilibrium probabilities. In practice, there is little difference between the two.

- _____ once a year
- _____ once every two years, or less

Value-Related Drivers

5. How would you rate the overall quality of the following airlines? (5 = "very high quality," 1 = "very low quality")
6. How would you rate the competitiveness of the prices of each of these airlines? (5 = "very competitive," 1 = "not at all competitive")
7. The airline flies when and where I need to go. (5 = "strongly agree," 1 = "strongly disagree")

Brand-Related Drivers (5 = "Strongly Agree," 1 = "Strongly Disagree")

8. I often notice and pay attention to the airline's media advertising.
9. I often notice and pay attention to information the airline sends to me.

10. The airline is well known as a good corporate citizen.
11. The airline is an active sponsor of community events.
12. The airline has high ethical standards with respect to its customers and employees.
13. The image of this airline fits my personality well.

Relationship-Related Drivers (5 = "Strongly Agree," 1 = "Strongly Disagree")

14. I have a big investment in the airline's loyalty (frequent flyer) program.
15. The preferential treatment I get from this airline's loyalty program is important to me.
16. I know this airline's procedures well.
17. The airline knows a lot of information about me.
18. This airline recognizes me as being special.
19. I feel a sense of community with other passengers of this airline.
20. I have a high level of trust in this airline.

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