

Incorporating Strategic Consumer Behavior into Customer Valuation

The calculation of customer value without regard to marketing policy is problematic because the value of managerial flexibility and the impact of consumer learning are neglected. This article develops a structural dynamic programming model of consumer demand that includes marketing variables and consumer expectations of promotions. The author uses the estimated parameters to conduct policy experiments that yield more accurate forecasts of customer value and to study the impact of alternative marketing policies.

A key idea in customer relationship management (CRM) is that customers should be treated as economic assets. An important corollary to this concept is that firms should identify their most profitable customers and then customize marketing on the basis of customer asset value. As such, the development of methods for forecasting customer value is of increasing importance. Thus far, the majority of customer valuation research has advocated techniques that require strong implicit assumptions about consumer behavior and marketing policies (Berger and Nasr 1998; Blattberg and Deighton 1996; Dwyer 1989). Typically, these techniques assume fixed marketing policies and deterministic retention and revenue rates.

Techniques that compute customer valuations without regard to marketing policy are problematic because they neglect the value of managerial flexibility and the potential for consumer learning. Managerial flexibility is important because as customers make decisions over time, firms can learn about individual customers and adapt marketing policies to the individual customer. However, if firms set policy as a function of transaction history measures, consumers can potentially learn from experience and strategically manage their decisions to receive advantageous terms.

In this article, I illustrate an approach to estimating customer asset value that uses concepts from the marketing science literature to account for several complexities and nuances of consumer behavior. Specifically, I estimate a structural dynamic programming model that replicates consumers' dynamic decision-making process (Erdem and Keane 1996; Gonul and Shi 1998). The model is capable of accounting for the effects of marketing variables, prior purchasing activity, consumer expectations of future promotions, and preference heterogeneity. The estimated parameters are structural in nature and are used to conduct policy experiments that simulate customer response to marketing policies over an extended time period. The simulation results provide an estimate of customer value that is directly connected to marketing decisions. The empirical results show that it is important to consider the complexities of

consumer behavior when analyzing customer asset value. Relative to a holdout sample, the simulation-based forecasts outperform standard methods in terms of absolute error and are better able to account for variation in long-term values in a heterogeneous customer base. Furthermore, by varying the prices and promotions used in the simulations, I can estimate the long-term consequences of alternative pricing strategies.

The primary contribution of the research is to the customer valuation literature. The results show how customer asset values are a function of marketing tactics, and they highlight the consequences of strategic decision making by customers. From a substantive perspective, the empirical findings are relevant to the issue of how to price over the stages of a customer relationship. This is an important topic because there is little work on individual-level dynamic pricing, despite the increasing ubiquity of CRM systems that facilitate individual-level marketing (Fudenberg and Tirole 2000). The specific problem I address herein is how to price dynamically to newspaper subscribers. Because the individual-level dynamic pricing policy is implemented with targeted promotional discounts, the results are also relevant to the literature that focuses on the long-term effects of promotions (Boulding, Lee, and Staelin 1994; Dekimpe and Hanssens 1999; Mela, Gupta, and Lehmann 1997; Nijs et al. 2001). This research adds to this literature with results from a novel category and by emphasizing the connection between promotional strategy and CRM.

I organize the article as follows: Next, I describe the empirical context of the study and highlight the logical structure of the demand model. Then, I report the estimation results and detail several policy experiments that forecast customer value for various marketing policies. I conclude with a discussion of managerial issues.

Customer Valuation and Dynamic Consumer Behavior

Customer lifetime value (CLV) is an established concept in database marketing and is growing in relevance to the broader marketing community (Berger and Nasr 1998; Gupta, Lehmann, and Stuart 2004; Jain and Singh 2002). It is typically computed with an equation such as

Michael Lewis is Assistant Professor of Marketing, Marketing Department, University of Florida (e-mail: mike.lewis@cba.ufl.edu).

$$(1) \quad CLV = \sum_{t=0}^T r^t (R_t - C_t),$$

where t indexes periods, r is the retention rate, R_t is the single-period revenue, C_t is the single-period cost, and T is the time horizon. Critical limitations of standard CLV formulas are that retention and revenue rates are not explicit functions of marketing actions and the firm's ability to adapt tactics based on observed customer behavior is not represented. The standard formulas also lack the ability to incorporate consumer learning and strategic customer decision making.

In this section, I develop a model of consumer behavior that replicates the dynamic nature of consumer decision making. The model includes elements of learning, an economic assessment of current-period choices, and expectations of the consequences of those choices. This model serves as the basis for a series of policy experiments that are designed to forecast customer value and to compare alternative dynamic marketing policies. By accounting for dynamically oriented consumer behavior and the influence of marketing variables, this approach overcomes many of the limitations in existing customer valuation methods.

The analysis uses transaction histories for 1578 customers of a major metropolitan newspaper. The data include monthly records of pricing, promotions, and subscription activity for each person. The average price in the data is \$2.40 per week and ranges from \$1.75 to \$3.00 per week. An important tactic for the firm is to acquire customers using reduced-rate introductory subscriptions. The typical practice is to use direct solicitation to offer prospects and lapsed customers short introductory subscriptions that are discounted by \$.50 to \$1.25 from the regular weekly price. Following the introductory subscription, customers are asked to renew at the full price. I divide the sample into a 1078-member estimation sample and a 500-member validation sample to test the predictive capabilities of several valuation methods.

The dependent variable of the model is the consumer's decision each month of whether to subscribe. The reward from buying during period t is labeled r_t , and it is assumed to be a function of marketing variables, such as price (P_t) and promotional solicitation (SOL_t). The reward associated with the no-buy option is normalized to zero. Although the decision modeled is a binary buy/no-buy choice, the context in which decisions are made depends on the customer's transaction history and the firm's tactics. For example, a promotional solicitation alters the decision environment for lapsed and prospective customers because a decision to buy when directly solicited is fundamentally different from a decision to resubscribe spontaneously. Likewise, the decision context for current buyers is different at the point of subscription expiration compared with the passive decision to continue to buy during a subscription term.

To account for the differences in context, I estimate separate response functions for each type of choice. I define four decision contexts: current customers at renewal, current customers in the middle of a subscription, solicited lapsed customers, and unsolicited lapsed customers. I use a

series of binary variables $d_j(t)$ to indicate whether a purchase is made at time t when the decision context is of type j . I use the $d_j(t)$ terms to define a summary variable $D(t)$, which indicates a purchase at time t , $D(t) = \sum_j d_j(t)$. The reward functions and decision indicators may be combined to create a convenient, time-specific reward term $R(t)$, defined as $R(t) = \sum_j r_j(t) \times d_j(t)$.

In addition to the effects of price and solicitations, consumer decisions may be affected by prior experience with the firm's marketing practices. To account for the effect of past pricing, I use current and past prices to compute a price-change variable $PINC_t = (P_t - P_{t-1}) / (P_{t-1})$. This price-increase term accounts for the possibility that reference price effects (Kalyanaram and Winer 1995) deters consumer demand beyond the effects of the actual price. In addition, I use two binary variables to track experience with prior promotions: $PSOL1$ is one if a customer has been previously solicited and is zero otherwise, and $PSOL2$ is one if a customer has received at least two promotional offers. The solicitation history variables are important in two respects. First, that a lapsed customer has been solicited previously may be important information because the decision to decline a promotion may indicate a lack of interest. Second, the use of promotions may influence a person's expectations of future promotions.

I account for consumer experience and loyalty with variables that track months as a current subscriber (F) and months as a lapsed customer (L). These variables are adjusted each month on the basis of a person's buying decision, as in Equations 2 and 3:

$$(2) \quad L(t+1) = L(t) + 1, \text{ if } D(t) = 0, \text{ and is } 0 \text{ otherwise.}$$

$$(3) \quad F(t+1) = F(t) + 1, \text{ if } D(t) = 1, \text{ and is } 0 \text{ otherwise.}$$

Rather than use these measures directly as covariates, I estimate different response functions for classes of experience. This approach eliminates the need for assumptions about the form of the relationship between experience and preferences (Berger, Bowman, and Briggs 2002). The empirical work uses four transaction history-based categories: long-term lapsed (and prospects), short-term lapsed, new customers, and long-term customers.¹ I index these categories by k and define them in Table 1. I index the reward functions, $r_{jk}(t)$, for transaction history category and choice context. These functions appear in Table 2 and vary

¹The four-category version outperformed specifications with additional categories based on the Bayesian information criteria (BIC).

TABLE 1
Transaction History Categories

Index	Category	Definition
$k = 1$	Long-term lapsed/prospects	$L \geq$ six months or new prospect
$k = 2$	Short-term lapsed	$L <$ six months
$k = 3$	New customers	$F <$ six months
$k = 4$	Long-term customers	$F \geq$ six months

TABLE 2
Choice Context-Specific Reward Functions

Decision	Reward Function
Current buyer at renewal (j = 1)	$r_{jk}(t) = \beta_{jk} + \beta_{price,jk} \times P_t + \beta_{pinc,jk} \times PINC_t$
Current subscriber (j = 2)	$r_{jk}(t) = \beta_{jk} + \beta_{price,jk} \times P_t$
Solicited lapsed customer (j = 3)	$r_{jk}(t) = \beta_{jk} + \beta_{price,jk} \times P_t + \beta_{sol,jk} \times PSOL1_t \times SOL_t$
Unsolicited lapsed customer (j = 4)	$r_{jk}(t) = \beta_{jk} + \beta_{price,jk} \times P_t$

in terms of the current and lagged marketing variables that are relevant. The β values are parameters to be estimated.

Marketing actions can also affect consumer decision making by changing expectations of the future availability of discounts. Of particular concern in this application is that consumers may learn from prior promotional activity and anticipate future discounts (Gonul and Srinivasan 1996). A customer's expectation of the probability of a promotional discount, $Pr(SOL)$, is modeled as a function of the consumer's previous experience with promotions:

$$(4) \quad Pr(SOL) = \frac{\exp(\gamma_0 + \gamma_1 \times PSOL1 + \gamma_2 \times PSOL2)}{1 + \exp(\gamma_0 + \gamma_1 \times PSOL1 + \gamma_2 \times PSOL2)},$$

where the γ terms are to be estimated. This expression gives the expected probability of a solicitation during the next month if a customer chooses to cease purchasing.

The inclusion of expectations necessitates a shift from a single-period choice framework to a dynamic model. I use a dynamic programming structure to replicate the decision-making process when dynamic considerations exist. The model includes factors that affect the merits of current options and a structure that includes dynamic elements. The objective function of a dynamically oriented customer making decisions in response to an evolving environment is

$$(5) \quad \max E \left[\sum_{t=1}^T \alpha^{t-1} R(t) | S(t) \right],$$

where $S(t)$ is a vector of information about the environment relevant to the customer's dynamic optimization problem, α is a single-period discount factor, and T is the horizon length. The state space vector $s(t)$ includes elements of the marketing mix and customer transaction histories.

The customer's decision problem involves selecting the option in each period that maximizes the expected utility for the remainder of the relevant time horizon. In dynamic programming terminology, the value function, V , is defined as the maximum value of discounted expected utility over the decision horizon. The alternative specific value functions $V_D[S(t)]$ are the expected values of buying ($D = 1$) or not buying ($D = 0$) at time t when the state space is $S(t)$ and then selecting optimal actions thereafter. The form of the alternative specific value functions is given in Equation 6, and it underscores that decisions are based on both the immediate reward provided by an alternative and the expected future utility from the next period onward.

$$(6) \quad V_D[S(t)] = E[R(t)|S(t)] + \alpha E[V[S(t+1)]|S(t), D(t)].$$

The first term is the current period benefit conditional on the current period state. The second term represents the value function of a process beginning one period in the future. A significant detail is that future benefits can depend on the alternative selected because the evolution of the state from $S(t)$ to $S(t + 1)$ may be conditional on the person's decision, $D(t)$. The relationship between the evolution of a customer's decisions and marketing policy is at the heart of this modeling approach. The customer's state includes transaction history elements, such as prior loyalty, prices, and promotions. Consumer decisions can affect the evolution of the state space by changing the loyalty profile observed by the firm, which may influence how the firm markets to the customer. If customers expect that a cancellation is likely to prompt a future discount, they can manage long-term utility by strategically buying and canceling.

Example

The dynamic structure of the model is best illustrated through an example of how expectations of future promotional discounts can affect multiple period decisions. I begin with a simple single-period reward function of the form $r(t) = \beta_0 + \beta_P P(t)$, where $r(t)$ is the reward from purchasing at time t , $P(t)$ is the price, and the β terms are response parameters. For the example, I also assume that the reward associated with not buying is equal to zero. In a single-period decision, a customer purchases if $\beta_0 + \beta_P P(t)$ is greater than zero.

To illustrate the dynamics, I assume that there is a two-period decision horizon and that the firm has the ability to offer individual consumers either the full price, P_F , or a discount, P_L . In a myopic decision environment, consumers for whom $\beta_0 + \beta_P P_F$ is greater than zero will purchase in both periods and earn a two-period reward of $2(\beta_0 + \beta_P P_F)$. However, when consumers expect promotions, they may engage in strategies that are designed to maximize cumulative rather than single-period rewards. If consumers expect that deciding not to purchase in the first period may result in being offered a promotional discount in the second period, some consumers for whom $\beta_0 + \beta_P P_F$ is positive may choose not to buy. If a consumer's expected probability of a promotional offer in the second period is $Pr(sol)$, the optimal two-period reward for the customer from not buying is

$$(7) \quad V_{No}(1) = 0 + Pr(sol) \times \max(\beta_0 + \beta_P P_L, 0) + [1 - Pr(sol)] \times \max(\beta_0 + \beta_P P_F, 0),$$

where $V_{No}(1)$ is the two-period reward associated with not buying in the first period and then selecting the optimal

action in the second period. Given the assumption that $\beta_0 + \beta_P P_F$ is positive, this can be reduced to

$$(8) \quad V_{No}(1) = \Pr(sol)(\beta_0 + \beta_P P_L) + [1 - \Pr(sol)] \times (\beta_0 + \beta_P P_F).$$

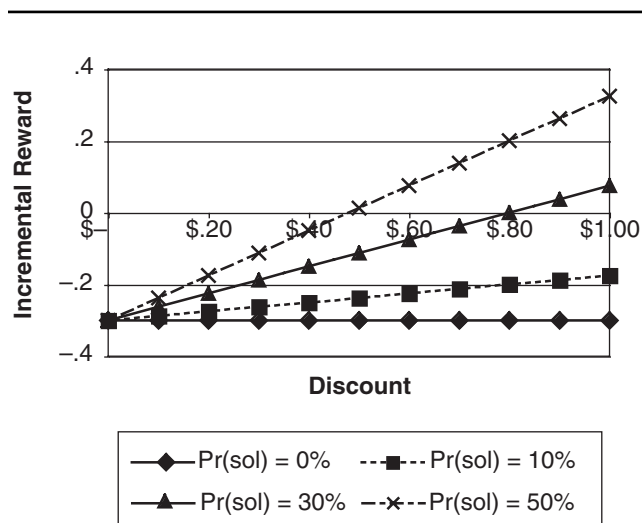
Customers benefit from strategic cancellations when $V_{No}(1)$ exceeds $2(\beta_0 + \beta_P P_F)$. Inspection of the expression for $V_{No}(1)$ reveals that the value of a strategic cancellation is based on the discounted price, P_L , and the consumer's expectation of being offered a promotion, $\Pr(sol)$. Figure 1 illustrates the relationship among promotion expectations, discount depth, and strategic cancellations for a two-period decision horizon, where β_0 equals 2.8, β_P equals -1.25 , and the full price, P_F , is \$2. In this example, observe that even consumers who gain a positive reward at the full price can benefit by strategically canceling if the discount or likelihood of promotions is sufficiently high. For example, if a consumer expects to receive a solicitation 50% of the time, a discount of \$.50 will motivate a cancellation in the first period. In contrast, if the expected probability is 10%, even a discount of \$1 does not lead to opportunistic behavior.

From the firm's perspective, this type of strategic behavior can reduce CLV and, thus, firm profitability. If the cost of serving a customer is C_T and the cost of solicitation is C_S , the reduction in the two-period profit from a customer who strategically cancels is

$$(9) \quad 2(P_F - C_T) - \Pr(S) \times [(P_L - C_T) + C_S] + [1 - \Pr(S)] \times \Pr(\text{buy}|P_F) \times (P_F - C_S),$$

where $\Pr(S)$ is the actual probability of a promotional offer, and $\Pr(\text{buy}|P_F)$ is the probability that the customer purchases at full price in the second period in the absence of a discount.

FIGURE 1
Incremental Two-Period Reward of Strategic Cancellation



Estimation

The estimation of model parameters is in some ways similar to the approach used in static choice models because the likelihood of observed choices is based on a comparison of the utility of the alternatives. The key distinction in dynamic programming models is that the utility of an alternative involves both current utility and expected future benefits. As such, choices are assumed to be the alternatives that maximize utility over the remaining horizon. If the error terms are distributed extreme value i.i.d., the probabilities of observed choices are given in Equations 10 and 11, where v is the deterministic portion of the alternative specific value functions (Rust 1994):

$$(10) \quad \Pr[D(t) = 1|S(t)] = \frac{\exp\{v_{D=1}[S(t)]\}}{1 + \exp\{v_{D=1}[S(t)]\}}, \text{ and}$$

$$(11) \quad \Pr[D(t) = 0|S(t)] = 1 - \Pr[D(t) = 1|S(t)].$$

The likelihood function is the sum of the logarithms of the choice probabilities defined in Equations 10 and 11. Therefore, estimation requires the repeated solution of a dynamic programming model to calculate the value functions. The estimation procedure involves nesting a dynamic programming algorithm within a maximum likelihood routine (see Rust 1994).

Thus far, I have assumed a population with homogeneous preference and expectations. To account for variability in preferences, I use a latent class approach (Kamakura and Russell 1989; Keane and Wolpin 1997; Lewis 2004). This approach assumes that the population consists of M distinct types with separate response functions. The use of a finite-mixture model to account for consumer heterogeneity increases the computational burden because the optimization problem must be solved for each population type.

Results

Table 3 presents estimated coefficients and standard errors for a specification involving the four transaction history classifications in Table 1 and two latent population types. The model also assumes that consumers use a three-month horizon.² This specification was selected from versions that varied in the number of transaction history classifications, the number of latent classes, and the extent of forward expectations.³ The results in Table 3 indicate two distinct customer types. Segment 1 represents only 5.1% of the population, and the parameter estimates suggest a propensity for members to shift back and forth between active and lapsed status. Segment 2 behaves more predictably and exhibits significant duration dependence.

The price sensitivity parameters of Segment 2 customers with fewer than six months as subscribers is -2.63 , whereas for customers with more than six months tenure,

²The two-segment model detailed in Table 3 required about four hours for estimation using a 2.4 GHz personal computer.

³The model in Table 3 was the preferred specification in terms of the BIC. Removing the expectations structure yielded a log-likelihood of -2181.7 and a BIC score of 7471.66 versus a BIC score of 7433.70 for the full model.

TABLE 3
Estimation Results

		Segment 1		Segment 2	
		Coefficient	Standard Error	Coefficient	Standard Error
Lapsed Six Months or More					
Solicitation	Intercept	2.21*	1.35	-.79*	.49
	Price	-3.95*	1.33	-5.71**	1.74
	Multiple solicitation	-.61	.99	.10	.32
No solicitation	Intercept	.72	1.52	-2.92	3.76
	Price	-2.50*	1.62	-6.07*	3.86
Lapsed Less than Six Months					
Solicitation	Intercept	.48	.86	-.52*	.33
	Price	-.85	1.26	-2.60*	1.08
	Multiple solicitation	-.47	.64	-.63*	.32
No solicitation	Intercept	-.73	2.14	-1.34*	.86
	Price	-3.06	2.39	-3.59*	.93
Tenure Less than Six Months					
Expiration	Intercept	1.40	1.91	2.22**	.64
	Price	-2.38	2.23	-2.63**	.71
	Price increase	-4.75*	2.60	-5.19**	.73
Subscription	Intercept	3.21*	.77	3.97**	.39
	Price	-2.42*	1.01	-3.30**	.42
Tenure Six Months or More					
Expiration	Intercept	.66	1.23	.99	1.34
	Price	-1.61	1.15	-.29	1.35
	Price increase	-9.18*	3.84	-9.16**	1.27
Subscription	Intercept	3.62*	1.56	3.78**	1.03
	Price	-3.06*	1.92	-2.51*	1.05
Expectations	Intercept	-4.15	4.25	-4.13	6.05
	Single solicitation	3.57*	1.99	2.02	1.89
	Multiple solicitation	.26*	.11	.15	.19
	Segment size	-2.93**	.30		
Log-likelihood		-2132.9			

* $p < .10$.
** $p < .01$.

the estimate is $-.29$. Similarly, price sensitivity increases as time lapsed increases. For customers who were lapsed fewer than six months, the estimated price parameter is -2.60 , whereas for those lapsed more than six months, the estimate is -5.71 . This pattern is consistent with findings that price sensitivity decreases with customer tenure (Reichheld and Teal 1996). In contrast, the price parameters of Segment 1 do not evolve in the expected manner. For customers with unexpired subscriptions, price sensitivity increases from -2.42 to -3.06 as tenure increases. For unsolicited lapsed customers, the estimated sensitivity decreases from -3.06 for the short-term lapsed to -2.50 for the long-term lapsed.⁴ These results suggest that this segment's members tend to buy and cancel opportunistically.

Other pertinent results include the effects of multiple solicitations and price increases. For multiple solicitations, the estimated coefficients are negative in all cases, but the majority of these estimates are not statistically significant.

⁴This pattern is supported only by directional evidence because many of the pricing terms for Segment 1 are insignificant.

The price-increase terms are negative and significant in all cases. Price increases are especially important for the long-term customers in Segment 2. For this group, there is minimal attrition unless the firm implements a price hike.

In terms of future expectations, the segments are fairly different. Segment 1 tends to exhibit a much stronger link between prior promotional activity and expectations of promotions than does Segment 2. This tendency is consistent with the characterization of Segment 1 as a switching segment. The results for Segment 2 show directional evidence that promotions increase the expectations of future discounts, but the effects are not significant. The expected probabilities of solicitations as a function of previous activity appear in Table 4.

Policy Evaluations

The parameter estimates from the dynamic programming model are structural in nature and therefore are policy invariant (Lucas 1976). As such, the estimates may be used to conduct policy experiments through simulation. Policy experiments may be used to calculate customer value and to

compare alternative marketing strategies that vary the depth and frequency of discounts.⁵

Table 5 compares the results for the holdout sample with forecasts from several valuation methods. The first row of the table uses average attrition rates, acquisition rates, and prices to forecast revenue. For a population with the same initial characteristics as the holdout sample, this procedure yields a mean customer value of \$75.17. The second row uses the average retention and acquisition rates for each level of the transaction history measures (L = time as a lapsed customer, and F = time as an active subscriber). This approach represents a migration model (Dwyer 1989) and predicts a mean value of approximately \$72 and a standard deviation of 33.6. The policy experiment uses the parameter estimates from the dynamic programming model and promotional and regular prices similar to the actual policies to

⁵To maintain clarity, I use a 36-month decision horizon, and I do not discount revenues. This horizon is long enough for dynamic factors to be important but short enough to mitigate concerns about the stability of the environment. I exclude costs and non-price revenues (advertising) from the forecast evaluation calculations but include them in the policy comparisons.

TABLE 4
Expected Probability of Promotional Solicitations

Previous Solicitations	Segment 1 (%)	Segment 2 (%)
0	1.5	1.6
1	35.9	10.8
2 or more	42.0	12.3

TABLE 5
Customer Valuation Comparisons

Customer Valuation Method	Mean Customer Value (\$)	Standard Deviation	Mean Absolute Error
Average retention and acquisition rates	75.17	8.18	33.45
Transaction history specific rates	71.63	33.55	16.73
Simulation based on dynamic programming model	78.55	53.86	8.68
Holdout sample	85.24	68.72	—

TABLE 6
Customer Valuation and Alternative Policies

Prices	Solicitations	Transaction History Classification				Average (\$)
		L ≥ 6 (\$)	L < 6 (\$)	F < 6 (\$)	F ≥ 6 (\$)	
Segment 1						
\$2.25, \$2.75	Random 5%	36.11	33.83	39.60	40.70	37.56
\$2.25, \$2.5, \$2.75	Random 5%	42.16	38.33	44.11	44.43	42.26
\$2.75	No promotions	32.28	28.86	35.41	35.63	33.04
\$2, \$2.5	Random 10%	52.63	48.68	54.76	56.16	53.06
Segment 2						
\$2.25, \$2.75	Random 5%	.02	3.03	28.81	89.25	30.28
\$2.25, \$2.5, \$2.75	Random 5%	1.37	5.00	60.23	89.25	38.96
\$2.75	No promotions	.27	2.07	38.77	102.27	32.21
\$2.25, \$2.5, \$2.75	Promote 1X	.69	13.33	52.15	96.01	40.55

simulate the behavior of a population that is identical to the holdout sample in terms of initial transaction history measures. The simulation predicts a mean value of \$78.55 and a standard deviation of 53.9.

The fourth row describes the actual 36-month revenue value of the holdout sample. The average customer value is approximately \$85 with a standard deviation of 68.7. The policy experiment is better able to capture variation because it uses more information related to marketing actions and consumer expectations than the other valuation methods. The benefits of including additional information are also reflected in forecast accuracy. In terms of forecast error, the policy experiment approach performs best with a mean absolute error of 8.7, compared with 16.7 for the migration method and 33.5 for the average rate-based calculations.

I report scenarios involving alternative marketing policies in Table 6.⁶ I provide separate valuation estimates for members of each latent population type (Segments 1 and 2). The base policy is a two-price policy involving a large acquisition discount (\$2.25 per week) that reverts to the full price after the initial subscription (\$2.75). This policy is similar to the pricing observed in the data. The second policy I evaluate is a three-price policy that uses an acquisition price of \$2.25 per week and offers a reduced rate of \$2.50 when the introductory subscription expires. The full price of \$2.75 is then offered at the second renewal. This strategy continues to invest in the relationship at a point (first renewal) when significant attrition tends to occur.

⁶For the customer valuation analyses, I use a cost-to-serve suggested by the firm and assume that solicitations cost \$1.

Table 6 reveals significant differences between the segments. The lack of variation in the valuations across the transaction history classifications for Segment 1 indicates that the transaction history measures provide little information. The similar valuations are due to the segment's tendency to move back and forth between active and lapsed states. For Segment 2, the long-term lapsed customers are of very low value, whereas long-term customers contribute approximately \$100 in profit. The three-price policy has a strong effect on new customers from Segment 2. For Segment 2, the value of customers who have purchased for fewer than six months increases from less than \$30 for the two-price policy to approximately \$60. If the population consists of an equal number of consumers in each transaction history classification, a weighted average of the effect of the three-price strategy on both segments predicts an increase in customer value of 27.6% relative to the two-price policy (\$39.12 versus 30.66). At the segment level, the three-price policy increases the value of Segment 1 members by 13% and Segment 2 members by 28.7%.

The third policy listed for the segments forgoes promotions and always charges \$2.75. For Segment 2, this policy increases the value of long-term lapsed and new customers. The increase in value of the long-term lapsed is due to greater solicitation costs under the base policy, whereas the greater value of new customers is due to the higher price at which customers are acquired. In the two-price policy, new customers are faced with a major price hike at first renewal, whereas in the no-promotion scenario, new customers already pay the full price. Therefore, the no-promotion policy results in greater customer values for new customers but at the cost of acquiring fewer customers. The lower acquisition rate is evidenced by the decrease in the value of lapsed customers from \$3 in the base policy to approximately \$2 for the no-promotion policy.

The fourth scenario listed for each segment is the best policy identified for that segment. For Segment 1, the suggestion is for lower prices and more frequent promotions. This type of policy is effective because it provides opportunities for Segment 1-type customers to engage in strategic purchasing behavior. A two-price policy that reduces acquisition and regular prices by \$.25 and doubles the promotion frequency increases average customer value by approximately 40% to \$53.06. For Segment 2, a three-price policy that restricts promotions to one time per customer increases the value of Segment 2 customers by 34% relative to the base two-price policy and by 4% relative to the three-price policy.

Thus far, the discussion has focused on the effects of different pricing and promotional strategies on each population type. I also forecast the relative benefits of applying the same policy across the entire population compared with customizing pricing at the segment level. The application of each segment's best policy results in an average customer value of \$41.20. In comparison, the base two-price policy yields a value of \$30.66, and the three-price policy results in an estimate of \$39.12. The application of the ideal Segment 2 policy across the entire population yields an average customer value of \$40.72. These are salient calculations because the benefit of using customized policies based on

unobserved types is estimated to provide an improvement of only 1.15% relative to applying the best Segment 2 policy across the population. However, it should be emphasized that the relatively minor benefit of customization based on latent segment type is due to the small size of Segment 1. The recommendation to customize policy only on the basis of observed transaction history measures (and not latent segment membership) is specific to this context and is not a general rule.

Figures 2 and 3 illustrate the relationship between price levels and buying probabilities. Figure 2 shows renewal rates as a function of acquisition price for the total population. Renewal rates are greatly reduced when customers are acquired through steep discounts. Customers acquired with a \$.75 weekly discount renew approximately 35% of the time versus a renewal rate of 80% for nonpromotionally acquired customers. Figure 3 shows how discounts influence acquisition rates. For the recently lapsed category, the acquisition rate ranges from 16% for a \$.75 discount to 4% for a \$.25 discount, and for the long-term lapsed category, the rate ranges from 6% to approximately 1%.

Discussion

In this article, I develop a structural dynamic programming model that can be used as a tool for valuing customer assets

FIGURE 2
Probability of Renewal Versus Acquisition Price

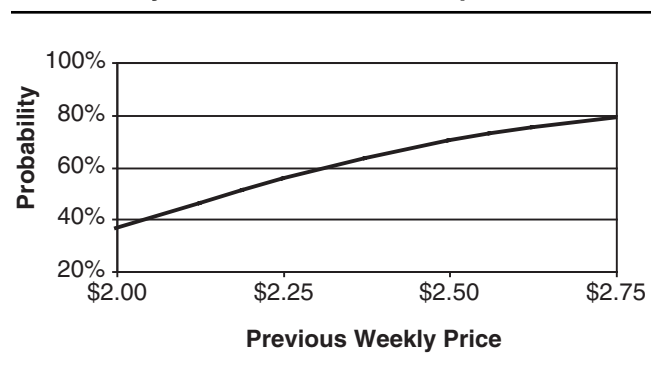
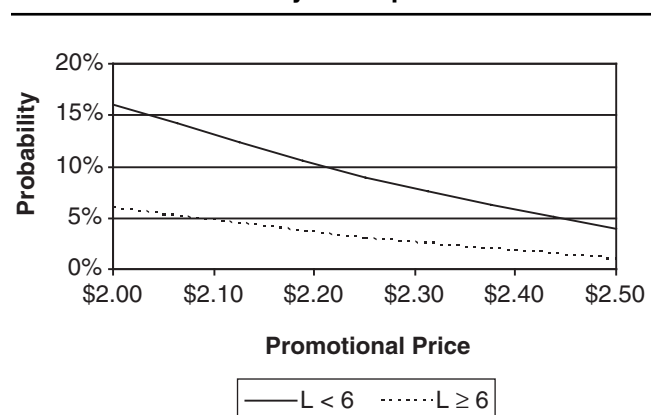


FIGURE 3
Probability of Acquisition



and comparing alternative marketing policies. This approach avoids the implicit assumptions about consumer behavior and firm policies that existing valuation methods use. The policy experiment-based approach evaluates the impact of alternative marketing policies and yields more accurate forecasts of customer value. From a substantive perspective, the results are relevant to audiences that are interested in pricing aspects of CRM. A strategy of gradually increasing prices is found to be more effective than a single steep acquisition discount. In terms of practice, there is support for this type of pricing strategy in the magazine industry (Freedman 1997).

An issue that merits further comment is the challenge and benefit of customizing marketing tactics on the basis of latent segments. Although the estimation results suggest different strategies for each segment, the identification of a customer's unobserved type is a nontrivial issue. Two approaches to determine latent segment membership are common. Observed choices for a given customer may be used to estimate the posterior probabilities of segment membership (Kamakura and Russell 1989), or alternatively, concomitant variables such as demographics may be used to predict segment membership (Gupta and Chintagunta 1994). In practice, a blend of these methods is likely to be used. The sample used for estimation could be segmented by posterior probabilities and then used to create demographic profiles for the latent segments. Demographics, actual or inferred from census data, might then be used to infer the "type" of new prospects, and inferences could be updated as the firm observes the customer over time.

Furthermore, although CRM systems frequently provide the means to customize marketing policies to increasingly

fine segments, there is reason to be concerned about potential consumer backlash. Customization of prices based on observable behavior or inferences about customer type is potentially controversial (Feinberg, Krishna, and Zhang 2002; Kahneman, Knetsch, and Thaler 1986). Although basing pricing on transaction history measures is generally accepted in categories such as subscription services (e.g., newspapers) or in industries in which loyalty programs provide quantity discounts, other price discrimination mechanisms may negatively affect customer relationships. For example, Coca-Cola earned negative publicity for testing vending machines that varied prices on the basis of the weather (Egan 2001), and Amazon.com came under fire in 2000 when consumers learned they were paying different prices for the same DVDs (Hamilton 2001). Because of adverse publicity, Coca-Cola chose not to implement the temperature-based pricing technology, and Amazon.com used refunds and apologies to placate consumers who were charged higher prices in the dynamic pricing experiment.

In the context of this article, although the firm can benefit by using aggressive promotions when managing the switching segment of the population, the estimated benefit from using latent-segment-specific pricing strategies is only a 1.15% gain in customer value. This increase must be weighed against concerns about negative publicity and consumer ill will. The relative benefit of using customized or one-to-one marketing techniques versus the possible adverse effect on customer relationships or consumer trust (Morgan and Hunt 1994) is a topic that merits additional research.

REFERENCES

- Berger, P., R. Bolton, D. Bowman, and E. Briggs (2002), "Marketing Actions and the Value of Customer Assets: A Framework for Customer Asset Management," *Journal of Service Research*, 5 (1), 39–54.
- and Nada Nasr (1998), "Customer Lifetime Value: Marketing Models and Applications," *Journal of Interactive Marketing*, 12 (1), 17–30.
- Blattberg, Robert and John Deighton (1996), "Manage Marketing by the Customer Equity," *Harvard Business Review*, 74 (July–August), 136–44.
- Boulding, William, Eunhyu Lee, and Richard Staelin (1994), "Mastering the Mix: Do Advertising, Promotion, and Sales Force Activities Lead to Differentiation," *Journal of Marketing Research*, 31 (May), 159–72.
- Dekimpe, Marnik and Dominique Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397–413.
- Dwyer, F. (1989), "Customer Lifetime Value to Support Marketing Decision Making," *Journal of Direct Marketing*, 8 (2), 73–81.
- Egan, Cathleen (2001), "Vending-Machine Technology Matures, Offering Branded Foods, Convenience," *The Wall Street Journal*, (December 13), B13.
- Erdem, Tulin and Michael Keane (1996), "Decision-Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Markets," *Marketing Science*, 15 (1), 359–78.
- Feinberg, F., Aradhna Krishna, and Z. John Zhang (2002), "Do We Care What Others Get? A Behaviorist Approach to Targeted Promotions," *Journal of Marketing Research*, 39 (August), 277–91.
- Freedman, Eric (1997), "Price-Raising Tricks of the Trade," *Folio*, 26 (8), 54.
- Fudenberg, Drew and Jean Tirole (2000), "Customer Poaching and Brand Switching," *RAND Journal of Economics*, 31 (4), 634–57.
- Gonul, Fusun and Meng Ze Shi (1998), "Optimal Mailing of Catalogs: A Methodology Using Estimable Structural Dynamic Programming Models," *Management Science*, 44 (9), 1249–62.
- and Kannan Srinivasan (1996), "Estimating the Impact of Consumer Expectations of Coupons on Purchase Behavior: A Dynamic Structural Model," *Marketing Science*, 15 (3), 262–79.
- Gupta, Sachin and Pradeep Chintagunta (1994), "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models," *Journal of Marketing Research*, 31 (February), 128–36.
- Gupta, Sunil, Donald Lehmann, and Jennifer Stuart (2004), "Valuing Customers," *Journal of Marketing Research*, 41 (February), 1–7.
- Hamilton, David (2001), "E-Commerce Special Report: The Price Isn't Right," *The Wall Street Journal*, (February 12), R8.

- Jain, D. and S. Singh (2002), "Customer Lifetime Value Research in Marketing: A Review and Future Directions," *Journal of Interactive Marketing*, 16 (2), 34–46.
- Kahneman, Daniel, Jack Knetsch, and Richard Thaler (1986), "Fairness as a Constraint on Profit Seeking Entitlements in the Market," *American Economic Review*, 76 (40), 728–41.
- Kalyanaram, Gurumurthy and Russell Winer (1995), "Empirical Generalizations from Reference Price Research," *Marketing Science*, 14 (3), 161–69.
- Kamakura, Wagner and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26 (November), 379–90.
- Keane, Michael and Kenneth Wolpin (1997), "The Career Decisions of Young Men," *Journal of Political Economy*, 105 (3), 473–522.
- Lewis, Michael (2004), "The Influence of Loyalty Programs and Short-Term Promotions on Customer Retention," *Journal of Marketing Research*, 41 (August), 281–92.
- Lucas, Robert E. (1976), "Econometric Policy Evaluation: A Critique," in *The Phillips Curve and Labour Markets, Vol. 1 of Carnegie-Rochester Conference Series on Public Policy*, K. Brunner and A.H. Meltzer, eds. Amsterdam: North-Holland, 19–46.
- Mela, Carl, Sunil Gupta, and Donald Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (May), 248–61.
- Morgan, Robert and Shelby Hunt (1994), "The Commitment–Trust Theory of Relationship Marketing," *Journal of Marketing*, 23 (October), 579–95.
- Nijs, Vincent, Marnik Dekimpe, Jan-Benedict Steenkamp, and Dominique Hanssens (2001), "The Category-Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1–22.
- Reichheld, Frederick and Thomas Teal (1996), *The Loyalty Effect*. Boston: Harvard Business School Press.
- Rust, John (1994), "Structural Estimation of Markov Decision Processes," in *Handbook of Econometrics*, Vol. 4, D. McFadden and R. Engle, eds. Amsterdam: North-Holland, 3081–3143.