Modeling Choice Behavior for New Pharmaceutical Products

Matthew F. Bingham, MS,¹ F. Reed Johnson, PhD,¹ David Miller, PhD²
¹Triangle Economic Research, Durham, NC; ²Glaxo Wellcome Inc, Durham, NC

ABSTRACT

This paper presents a dynamic generalization of a model often used to aid marketing decisions relating to conventional products. The model uses stated-preference data in a random-utility framework to predict adoption rates for new pharmaceutical products. In addition, this paper employs a Markov model of patient learning in drug selection. While the simple learning rule presented here is only a rough approximation to reality, this model nevertheless systematically incorporates important features including learning and the influence of shifting preferences on market share. Despite its simplifications, the integrated framework of random-utility and product attribute updating presented here is capable of accommodating a variety of pharmaceutical marketing and development problems. This research demonstrates both the strengths of stated-preference market research and some of its shortcomings for pharmaceutical applications.

Keywords: Bayesian updating, choice, consumer preference, Markov, pharmaceutical marketing, Random-utility

Introduction

Traditional factors influencing the acceptance of a novel pharmaceutical compound include levels of safety and efficacy observed in clinical trials. While the importance of these factors remains undisputed, cost differentials mean that clinical data may not provide sufficient information for evaluating treatment options [1]. Decisions involving tradeoffs among efficacy, toxicity, and costs customarily are made using judgment methods derived from past successes and failures [2]. However, natural experiments provided by historical adoption rates of drugs with known properties provide limited information on likely consumer demand for novel pharmaceutical compounds.

This paper outlines a decision model for evaluating the impact of information regarding alternative treatments, toxicity, uncertainty regarding effectiveness, delivery method, and cost on demand for unique compounds. Any approach to pharmacoeconomic evaluation requires specification of a viewpoint to facilitate comparison [1]. Relevant decision-makers in this model include those groups interested in pharmaceutical demand forecasts. These groups could include pharmaceutical developers, marketers, and pharmacy and therapeutic (P & T) committees faced with a difficult formulary listing decision.

A number of legitimate concerns limit the usefulness of traditional pharmacoeconomic methods in this arena. These concerns include potential lack of objectivity, disregard of closely substitutable products, extrapolation from irrelevant populations, ignoring dynamic aspects of drug choice, and other methodological issues. Shortcomings in these areas limit the usefulness of cost effectiveness (C-E) studies for comparing competing drugs in a therapeutic class. This situation can lead to decision-making based almost solely on drug cost [3]. The increasingly competitive health care market may put those focusing on patient satisfaction at a disadvantage.

Rising competition in health care has led to a growing concern for understanding consumer preferences. The increasing importance of a demand perspective in drug development, marketing, and formulary listing decisions highlights the need for a quantitative measure of value from the point of view of health-care consumers. The method presented here draws its structure from choice theory, a fundamental description of consumer behavior. Modeling market-research data within this framework allows estimating the parameters underlying individual preferences. Combining these estimated parameters with price and outcome information from related products in a random utility framework
makes it possible to forecast initial consumer demand for a new pharmaceutical compound.

Pharmaceutical consumers face uncertainty arising from imperfect information regarding product attributes [4]. For this reason, forecasts of initial demand may be of limited value. Specifically, as consumers gain experience it is reasonable to expect that they will incorporate previously learned information in current and future decisions. Of course, consumers face uncertainty in many product markets. However, the consequences of poor selection in the pharmaceutical market often are more severe and immediate than corresponding decisions in conventional markets. Thus, any approach hoping to generate future pharmaceutical demand forecasts must consider the effect of prior experience on subsequent choices. Here, we integrate a random-utility decision rule with Bayesian updating in a discrete Markov process. Because this framework explicitly considers the influence of prior pharmaceutical experience on future choices it is able to generate demand forecasts for future time periods superior to forecasts arising from static models.

**Methods**

**Multi-Attribute Utility Theory and Health-State Preferences**

The traditional utility maximization model provides a framework for analyzing consumer response to price and income changes. However, this theory is mute with respect to preferences for nonexistent or new goods. To explain consumer reactions to quality changes or the introduction of new products, Lancaster advanced the concept now known as multi-attribute utility theory [5]. Lancaster’s underlying tenet is that commodities themselves do not provide utility to the consumer. Rather, commodities typically are composed of multiple attributes contributing to satisfaction. Health outcomes arising from pharmaceutical interventions can be thought of as multi-attribute commodities. The attributes associated with drug use might include changes in symptoms, experienced, mobility, and physical or social functioning levels. The utility realized by consumption of a given drug thus can be expressed as a function of the health-outcome attributes associated with its use. Therefore, demand for a pharmaceutical compound is determined by preferences for the health states associated with its consumption [6]. In practice, the utility associated with a particular treatment is often expressed as a function of drug characteristics, patient characteristics, and health-outcome attributes.

**Quantifying Health-State Preferences**

Health-care researchers have recognized the multidimensional nature of health status in developing health-status indices. Multi-attribute systems provide a concise and comprehensive framework for describing health states. Such indices typically consist of a number of health attributes. Each attribute is composed of multiple levels. A unique combination of attributes and their associated levels comprises a health state. Utility weights provide the only means of incorporating consumer preferences in the decision model presented here. For this reason, selecting the correct weights is vital. In general, useful utility weights arise from adherence to economic principles, careful preference elicitation, and judicious selection of an appropriate health-status index. The weights typically estimated from health-status indices suffer from a variety of limitations in these areas. For example, estimating weights from the Quality of Well-Being index assumes additive utility independence. This requirement disallows diminishing marginal utility and interaction effects for multiple health outcomes. These restrictions result in incorrect conclusions at the extremes of the health attribute space [7].

The development of health-utility indices demonstrates the potential for estimating utility weights from experimental data. Unfortunately, these indices are not often flexible enough to incorporate important aspects of utility theory. Thus, the validity of estimated utility weights using standard methods such as QALYs is questionable. Because of these limitations, we propose developing weights from a stated preference (SP) survey. The weights developed from a conjoint style SP survey are capable of representing preferences in a manner consistent with economic theory [8]. In particular, SP techniques allow both diminishing marginal utility of health and estimation of weights for combined health states [9]. An additional advantage of SP techniques is the ability to include health-cost as an experimental attribute. This feature allows conversion of marginal utilities to marginal dollar values.

The rigorous utility-based foundations of SP techniques and the extensive implementation of conjoint analysis for traditional product development suggest the promise of this technique for evaluating health-state preferences in a utility-theoretic manner [10]. Like other survey methods, SP techniques are not insulated from concerns about the reliability of estimated weights. However, there is some evidence that describing health-state attributes in specific and familiar language leads to reliable estimates. Finally, it is important that the utility weights
capture relevant aspects of individual preferences. The required level of responsiveness is most likely obtained by employing a health-status index that is sufficiently detailed and inclusive to capture relevant variations in anticipated outcomes. These complications underscore the importance of careful survey development.

SP has already seen some use in valuing health states [9,11–13]. Figure 1 illustrates a recent choice-format SP designed to elicit respondent tradeoffs among episode duration, symptom, daily activity limitations and cost. Choice formats mimic consumer decision-making most closely. Other formats commonly used for eliciting preferences include rated or graded pairs and rankings. All formats employ an experimental design in which respondents compare a series of attribute bundles.

Each respondent evaluates a series of such screens that show various combinations of choices. Using a properly specified orthogonal design, resulting data can be analyzed to recover underlying health-state utility parameters of interest. Combining these utility weights with choice attributes provides estimates of the expected utility associated with each choice. These expected utilities provide the foundation for predicting choice behavior under specified conditions. The following sections outline the conceptual and empirical basis for such analysis.

**Stated Preferences and Expected Utility**

Careful preference elicitation and utility-weight estimation facilitate accurate representation of health-state preferences. For the remainder of this paper, we will assume that these preferences are exhibited by rational, utility-maximizing consumers. Under these assumptions, the utility derived by using drug i is a function of x, discrete adverse health attributes, s = 1, . . . , S, and y, discrete beneficial health attributes, t = 1, . . . , T.

\[
U_i = U(x_{i1}, \ldots, x_{iS}, \ldots, x_{iS+t}; Y - c_i) \quad (1)
\]

where Y is disposable income and ci is the patient’s cost of drug i. The marginal utility of attribute s, \(\partial U_i/\partial x_s\), is negative and the marginal utility of attribute t, \(\partial U_i/\partial x_t\), is positive. Under these conditions, a standard multinomial logit model employing pharmaceutical product characteristics and outcome expectations as explanatory variables provides the basis for predicting drug choice.

In general, researchers will be interested in consumer preferences about several drug attributes. Introducing multiple attributes adds complexity to determining utility. This complication arises because utility is a function of each attribute. In practice, determining utility can be simplified by assuming some form of utility independence [7]. Utility independence implies that preferences for a given attribute are invariant with respect to levels of other attributes. When all attributes in a multi-attribute utility function exhibit this quality the attributes are said to be mutually utility independent. This simplifying assumption allows estimation of utility-theoretic parameters without requiring evaluation of every possible attribute combination. Under the assumption of mutual utility independence the utility of treatment alternative i can be expressed as a linear combination:

\[
U_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \quad (2)
\]

Here the x’s are measures of alternative treatment attributes. The betas (\(\beta\)) are utility weight parameters estimated from experimental data.

Assuming mutual utility independence greatly simplifies utility determination without forcing unreasonable utility restrictions. In particular, it is important to note that this assumption does not disallow estimating attribute interactions. In fact, the specification considered in equation 2 could be generalized to account for this complexity. In particular it is not required that each x represents a single attribute. Rather, an SP experiment can be designed such that some of the x’s represent the interactive effects of certain health-state attributes. The most general form is a completely expressed multilinear utility function [14]. This specification
requires utility weights for every possible interaction. For this reason, the associated measurement task is quite intensive. A more likely specification might employ an experimental design specifically developed to allow estimating interactions for pairs of variables that researchers believe to be either substitutes or compliments.

Utility weights measure the relative importance of specific health attributes in determining health-related utility. However, health outcomes arising from pharmaceutical interventions do not occur with certainty. Rather, outcome attributes typically occur with some probability. The relevant probabilities are those that consumers believe are associated with each attribute. In the presumed absence of this knowledge, information arising from clinical trials or other sources can be substituted. Individual interpretation of these probabilities is an important component of expected utility determination deserving appropriately serious consideration in model development. Here, \( p_{ij} \) represents the probability of an attribute’s occurrence. If each attribute occurs independently of all the other attributes, the probability of observing some realized attribute combination \( X_j \) is

\[
P_i(X_j) = \prod_{j \in X_j} p_{ij} \quad (3)
\]

Expected utility is the probability-weighted sum of all possible outcome combinations \( X_j \).

\[
V_i = \sum_j P_i(X_j) \cdot U(X_j) \quad (4)
\]

This framework takes on behavioral content by introducing utility maximization. We assume that consumers choose drug \( i \) when \( V_i = \max(V_1, \ldots, V_k) \). Here, \( V_k \) is the perceived expected utility of each of \( K \) drugs in the choice set. The choice set is limited to technically feasible alternatives, alternatives that satisfy regulatory requirements, and alternatives having \( c_i \leq Y_{ih} \) where \( Y_{ih} \) is health-related budget and \( c_i \) is the cost of each drug. The \( V_k \) are summary measures that account for the desirability of each feasible alternative relative to competing alternatives in the choice set.

Results

Simulating Choice Probabilities From a Random Utility Model

Simulating aggregate choice behavior from estimated utility functions requires a rule for predicting behavior. One such rule widely used in market research is that the option associated with the highest expected utility will be an individual’s first choice. Simple algorithms of this sort ignore the probabilistic nature of the choice process. Methods that consider the error properties of choice data address this shortcoming [15]. Thurstone’s random utility concept allows the possibility that choice is not determined solely on the basis of known preferences and decision rules [16]. This realization is incorporated into the present model by allowing a residual term to represent the effect of unobserved factors on perceived utility. These factors can include imperfect information about drug attributes and outcome probabilities, as well as unobserved variations in tastes and random errors among decision-makers. Viewed in this manner individual \( j \)’s perceived expected utility is the sum of systematic and random components.

\[
V_i = E(U_i) + \varepsilon_i \quad (5)
\]

Utility maximization subject to constraints forms the basis for random-utility theory. However, an observed choice does not always represent the alternative with the highest utility. Rather, this option has the highest sum of systematic and random utility components. The random component allows the realistic possibility that any allowable alternative will be chosen only with some probability. At the same time, random utility precludes the possibility that an option always dominates all others in the choice set. Evaluating choice probabilities in this framework requires quantifying expected utilities and specifying the associated error distribution. McFadden integrated the concepts of random utility and evaluation of commodity attributes to develop a multinomial logit model of discrete choice. McFadden’s random utility specification assumes that the residuals \( \varepsilon_i \) are independently and identically distributed with the type I extreme-value distribution whose cumulative distribution function is \( \exp(-e^{-\varepsilon_i}) \). The empirical choice probabilities for this random-utility model (RUM) are described by

\[
\text{Prob}(\text{chosen}|X, Y, c) = \frac{e^{V_i}}{\sum_{k=1}^{K} e^{V_k}} \quad (6)
\]

It follows that the predicted proportion of choices favoring drug \( i \), or market share \( S_i \), is
where \( n \) denotes individual \( n, n = 1, \ldots, N \). Note that the market share predictions of equation 7 depend upon the influence of individual characteristics on drug choice. Because SP surveys allow estimating individual specific models this specification is technically correct. However, if individual data is either irrelevant or unavailable, market share prediction is correctly specified by equation 6.

Originally, economists used discrete-choice models combined with multi-attribute utility theory to explain observed market choices. Applications include transportation, communications, consumer purchases, and environmental economics [17–20]. However, marketers soon recognized the value of using discrete-choice modeling techniques to analyze data generated by hypothetical choice experiments. In these experiments, respondents choose among groups of attribute profiles. As in market data, multi-attribute utility theory provides the foundation for product profiles. However, the hypothetical nature of such experiments allows evaluation of novel attributes and attribute levels. Experiments of this sort provide a well-accepted framework for estimating the demand effects of product differentiation in traditional product markets [21].

Employing market data to forecast demand for unique pharmaceutical products suffers from some limitations similar to those occurring in traditional product markets. Specifically, innovative and developmental drugs typically include features not available in the marketplace. Thus, market data cannot be used to evaluate consumer preferences for these attributes or pharmaceutical profiles including them.

When field surveys are employed to collect data, the parameters of \( V_k \) are estimated from an appropriate sample of observed choices. This paper demonstrates the possibility of using stated-preference data to estimate these parameters. Unlike observed market choices, data elicited in a hypothetical choice experiment allows the possibility of evaluating preferences for innovations. Specifically, assuming a general, preference-based form for health-related utility allows direct estimation of the utility weights associated with pharmaceutical attributes and the health outcomes anticipated to arise from pharmaceutical consumption. Choice probabilities can then be simulated by setting \( \epsilon = 0 \) in a random utility framework and manipulating pharmaceutical attributes. Employed in this manner, the model is capable of analyzing the impact of a variety of factors including cost, outcomes, and competition on anticipated drug adoption rates.

Like many traditional marketing studies, the model presented here employs information arising from a consumer-based, SP survey. This simplification assumes that patients alone determine the demand curve for prescription medications. Of course, the essence of the prescription process involves the doctor-patient relationship. Correctly modeling patient–doctor interaction is a challenging and important component to determining drug demand. It is generally assumed that doctors select the drug they believe is best suited to their patient's condition. Stern and Trajtenberg and Crawford and Shum provide insight into this relationship [22,23]. The model presented here assumes that the physician knows patient preferences and acts according to his interests. Thus, like Crawford and Shum, we view decision-making agents as patient-doctor units attempting to maximize patient utility in each period. The following section provides a numerical simulation demonstrating the capabilities of this model.

**Numerical Simulation**

Measuring SP preferences for pharmaceuticals requires a systematic framework to characterize relevant products with respect to a comprehensive set of attributes and attribute levels. Demand for pharmaceutical products arises directly from preferences for product attributes and indirectly from preferences for the health states realized by their consumption. Thus, attributes and levels must encompass the variety of health outcomes and product attributes associated with drug administration in a particular disease state. Once attributes and levels are determined they can be combined into health-state bundles, which are used in an SP exercise. Figure 2 illustrates attributes and levels for a simulation assessing demand for competing migraine treatments.

Stewart and colleagues have determined that 17.6% of women and 5.7% of men suffer from migraine attacks [28]. The onset of migraine attacks usually occurs between the ages of 25 and 55 [27–30]. The median attack rate among migraineurs ranges from 0.4 to 1.5 attacks per month.
Thus, learning is an important component of migraine drug selection. Integrating learning through relief probability updating with random-utility maximization provides a realistic approximation to real-world decision-making. Using simulated data provides an idea of model capabilities when error structure and functional form are known. Successive choice simulation demonstrates the model’s capability of generating expected penetration rates for a group of migraine medications after six months.

A primary difficulty associated with employing SP data for pharmacoeconomic market simulations of this sort arises from the uncertainty associated with outcomes. This is particularly true for untried products. For example, a migraine medication with an efficacy rate of 70% provides effective symptom relief for about 70% of patients across patients per attack. Longitudinal analysis within patients suggests that efficacy rates often vary by patient. Thus, on any given migraine attack, some patients will have a higher probability of responding, some will have a lower probability, but on average, 70% of patients will experience some relief. Neither the physician nor the patient knows what the probability will be for a specific patient or for a particular attack. Thus, there is imperfect information about product attributes. In the absence of perfect knowledge, it is natural to substitute clinical data for expected probabilities of relief or adverse outcomes. This simplification probably represents a realistic approximation for first-time decision-making. However, it is doubtful that a patient who has experience with a drug retains clinical trial efficacy data as their subjective response probabilities. Rather, it is likely that patients form a new expectation based on their prior beliefs and their experience with the drug.

Despite the important influence of uncertainty and learning on pharmaceutical demand, empirical evaluations of these factors are scarce due to data limitations. In general, the aggregate market-share data employed in pharmaceutical demand studies do not provide the patient-level information required to analyze decision-making under uncertainty [24,25]. However, in a departure from the static approach dictated by aggregate data, Crawford and Shum employ a patient-level panel dataset to investigate the dynamics of uncertainty and learning in the Italian market for prescription antulcer drugs [23]. Results indicate that Bayesian updating provides an effective structure for modeling patient’s incentive to learn about the effectiveness of various drugs.

For the simulation, we employ an empirical version of Bayes Rule that makes updated expected relief probabilities a weighted average of information from the two most recent periods in the following manner:

$$E(\text{RESPPROB}_{t}) = w_1(\text{RESP}_{t-1}) + w_2(\text{RESPPROB}_{t-2})$$

(8)

where \(\text{RESPPROB}_{t-2}\) is the subjective expected response probability in period \(t-2\) and \(\text{RESP}_{t-1}\) is the patient’s actual experience in period \(t-1\). This simple scheme provides an example of one way to include learning in a model of drug adoption. Here, we consider learning as it relates to effectiveness. Incorporating additional opportunities such as the probability of experiencing an adverse event could extend the model. In addition, it is important to note that because the simple updating rule used here does not vary by individual, simulation does not require drawing from any particular distribution. A more detailed specification might include the possibility of variation in updating. However, this model intends to forecast market share. Mean values of updated probabilities are sufficient for this purpose. Below is an illustration of this Bayesian updating scheme integrated with random-utility maximization.

Consider a patient without prior experience with migraine medications. With the assistance of a physician the patient selects a migraine medication with a particular attribute profile according to random-utility maximization. Here, the Response Probabil-

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response Time</td>
<td>Fast</td>
<td>Within one hour</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>About one and one half hours</td>
</tr>
<tr>
<td></td>
<td>Slow</td>
<td>About two hours</td>
</tr>
<tr>
<td>Relief Probability</td>
<td>High</td>
<td>90% probability of relief</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>75% probability of relief</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>45% probability of relief</td>
</tr>
<tr>
<td>Delivery System</td>
<td>Injection</td>
<td></td>
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<tr>
<td></td>
<td>Intranasal</td>
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<tr>
<td></td>
<td>Oral</td>
<td></td>
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<tr>
<td>Recurrence Probability</td>
<td>High</td>
<td>40% probability of recurrence</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>30% probability of recurrence</td>
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<tr>
<td></td>
<td>Low</td>
<td>5% probability of recurrence</td>
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<tr>
<td>Costs</td>
<td>High</td>
<td>$30</td>
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<td></td>
<td>Medium</td>
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<td></td>
<td>Low</td>
<td>$10</td>
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</tbody>
</table>

Figure 2 Attribute and attribute levels shown in choice comparisons.
ity attribute level of the selected migraine medication is represented by the percentage of clinical trial patients who experienced migraine relief when employing this particular medication. Using the medication results in the patient either experiencing or not experiencing relief. Naturally, the outcome associated with using the drug influences the patient’s subjective expected relief probability associated with the drug. Here, we assume that the expected relief probability is an equally weighted average of the prior relief probability and the most recently realized outcome. For example, consider a drug (Drug A) with clinical efficacy of 70%. A first-time patient evaluates the relief probability of this drug at 70%. If the patient chooses drug A and experiences relief in the first period, he updates the relief probability of the drug to an equally weighted average of 70% and 100%, or 85%. Thus, success with a given medication in prior periods increases the likelihood of its selection in subsequent periods. Similarly, failure results in a downgrading of expected relief and a lower likelihood of selection. This simple scheme provides an example of one way to include learning in a model of drug adoption. The updating rule we have chosen is intended to be illustrative rather than representative. However, the fast-acting nature of migraine medication and the difficulty of predicting relief for a given attack support the structure of the learning process demonstrated here.

This updating process takes place each time a patient suffers from a new attack. Thus, if a medication is effective, the patient’s subjective expected probability of relief increases and it is more likely that the patient will choose that medication again. If it is ineffective, the individual downgrades expected relief probability and the corresponding expected utility. We employ here the assumption that the individual maximizes random utility with each new episode. Successes (failures) lead to upgrading (downgrading) of selection probabilities. Naturally, forecasting accuracy depends upon how closely the rule used for prediction approximates market behavior. Rust demonstrates that combining a known utility function with market data provides sufficient information for estimating such rules [26].

Our simulation looks at a cohort of patients first suffering from migraines. The duration considered in such a model depends upon computational constraints and the information required for a particular study. This particular simulation takes place over six months and assumes each group member faces an average of three decision-making opportunities. Migraine data indicate that sufferers are likely to face more than three migraines over a six-month period. However, we consider the possibility that headaches spontaneously resolve before treatment by including only three decision-making opportunities. At each stage of this process, decision-makers maximize random utility based on assumed utility weights. We have shown that these utility weights could be estimated from a suitably designed and administered SP survey. For simplicity, we consider only three drugs. The simulation is complicated by the fact that drug attributes, in particular expected relief probabilities, vary by episode and individual (or group). For this reason, we introduce the notational convention that $A_{ij}$ represents the attribute profile of drug A for episode i and individual j. Note, however, that all individuals are initially endowed with the same set of prior beliefs regarding effectiveness and an identical updating process. Thus, the three-episode decision-making process for individual j (or group j) can be graphically depicted as follows in Figure 3.

Note that the preceding illustration consists of a finite number of states where the probability of moving from one state to another is known. Markov decisions processes (MDP) provide a means for modeling such behavior over time. Markov models consist of state variables $s_t$ and control variables $d_t$. These variables are indexed over time $t = 0, 1, 2, 3, \ldots , T$. In the case considered here, data from the above illustration takes the form $\{d_{it}, s_{jt}\}$. Here, $d_{it}$ and $s_{jt}$ represent the decision and state of agent j at time t. In the above illustration, the state and corresponding decision of agent j at a given time are represented by the block-arrow combination associated with that state. Note that both attribute perceptions and expected utilities are path-dependent. That is, levels of expected relief probability for Drug A depend upon both the initial state (efficacy rate) and experience (perceived effectiveness). Therefore, the optimal decision at time t depends not only on the current state $s_t$, but also on the history of the process, $d_t = d_t^T(s_t H_{t-1})$ where $H_t = (s_0, d_0, \ldots , s_{t-1}, d_{t-1})$.

Despite this complexity, once an individual arrives at a state, the model retains the Markovian feature that the current optimal decision depends on process history only through its influence on the current state. Thus, the optimal decision depends only upon the current state $s_t$: $d_t = d_t^T(s_t)$. Our model reflects this property through the influence of history on the expected relief probability associated with each migraine medication. Expected relief probability levels and associated Markov states are determined by the history of choices, specifi-
Figure 3 Three-episode decision-making process:

Decision 1. Individual $j$ has not previously sought treatment for migraines. Thus, individual $j$ chooses drug B (Decision 0) based on random-utility maximization and attributes of all drugs. Expected response-probability attributes for all drugs are efficacy rates arising from clinical trials.

Decision 2. Individual $j$ treats the second migraine with Drug A. He then updates the expected relief probability for drug A based on experience in State 2. The individual retains the expected relief probability for drug B from State 2. The expected relief probability for drug C still arises solely from clinical trials data. The individual then chooses drug C (Decision 2) based on random utility maximization and attribute levels of all drugs. At this point the simulation concludes, and individual $j$ is assigned to Drug C.

Decision 3. Individual $j$ treats the migraine using drug B. The individual then updates expected relief probability for drug B based on experience in State 1. Individual $j$ then chooses drug A (Decision 1) based on random utility maximization and attribute levels of all drugs. The response-probability attribute for drug B ($P_b$) is updated but $P_a$ and $P_c$ are still efficacy rates. In the third period, individual $j$ treats the third migraine with Drug C.

cally, successes and failures experienced by each migraine sufferer. However, once attribute levels are established for a given state, random-utility maximization and hence decision-making depend only on the expected utility associated with each drug.

The preceding example demonstrates individual decision-making in a Markov model of learning behavior. This process forms the basis for determining aggregate behavior required to estimate market penetration over time. Determining aggregate behavior requires iteratively estimating the percentage choosing each drug by period. Successive iterations divide the original population into percentages anticipated in each Markov state. Period two decisions produce percentage estimates for each state in period three. Summing these percentages by drug returns an estimate of market penetration for each drug in the third period.

For the following example, we assume knowledge of the parameters describing health-related utility. We simulate data under the assumption of these known parameters and Equation 7. Using these simulated data, we recover estimated parameters by fitting a random-utility model. Choice probabilities for the first stage then are simulated by setting $e_i = 0$ in the random utility framework (see equation 7). This procedure generates the expected percentages of patients selecting each medication the first time they seek treatment. These percentages represent expected market share in the first time period. At this point, single-period market forecasts of this sort are complete. However, imperfect knowledge of product attributes and learning from experience mean that future choices depend upon realized outcomes. Thus, choices are likely to change over time. The expected percentage of patients responding (and not responding) to treatments are used to determine outcomes. In this illustration, these percentages are arbitrarily chosen. In an actual application, it is expected that the analyst will use the best available prediction of effectiveness.

Once outcomes have been determined, each group updates relief expectations according to the version of Bayes’ rule described earlier. This procedure results in six groups of patients. Although each of these six groups can evaluate the expected relief probability differently, each group still only considers three drugs at each choice occasion. After having an experience with a drug in period one, migraine patients reconsider their choices employing information learned in period one to influence choices in period two.

For the simulation, we employed a $3^4 \times 2^2$ orthogonal design to represent four migraine drug attributes with three levels, these include response time, relief probability, reoccurrence probability, and cost. Delivery system is oral, nasal, or injectable. Thus, in the experimental design, delivery system is a categorical variable represented by binary variables for nasal and injectable delivery where oral delivery is the omitted category. At this point, we postulate a set of parameter values and simulate random-utility data accordingly. Our simulated data employs 5000 responses. Thus, these simulated data might represent the hypothetical responses of 500 survey participants answering 10 choice questions. Each choice question consists of two drug profiles. The expected utility of each drug profile is generated mathematically using hypothetical drug pro-
files, postulated parameter values, and an additive random utility term. Our hypothetical survey subjects select the profile with the highest sum of systematic and random utility components. Survey responses and hypothetical drug profiles comprise the data used in multinomial logit estimation. The postulated and estimated parameter values are as follows in Table 1.

For this example, we consider three drugs. The patient population being evaluated has not previously suffered from migraines. Thus, they employ only clinical-trial response data on the first choice occasion. Entering period one, the drug profiles are as follows in Table 2.

Simulating choice probabilities in a random-utility framework results in division of the original population into three groups depending upon drug choice. Percentages choosing each drug are simply the choice probabilities arising from the random-utility formulation. After one period, the cohort of migraine sufferers falls into one of six groups depending upon the drug they chose and its success in relieving the migraine. Period one probabilities are established using random-utility maximization in the following manner.

**Period One Probabilities**

\[
P(A_i) = \frac{\sum_{n=1}^{N} P(A \text{ chosen}|X_n, Y_n, c_n)}{\sum_{n=1}^{N} \sum_{k} e^{V_{kn}}}
\]

\[
P(B_i) = \frac{\sum_{n=1}^{N} P(B \text{ chosen}|X_n, Y_n, c_n)}{\sum_{n=1}^{N} \sum_{k} e^{V_{kn}}}
\]

Period two probabilities are established by random-utility maximization using updated response probabilities from period one. After two periods, the cohort of migraine sufferers falls into one of 36 categories. The defining feature of each category is the level of the expected response attribute for each drug. In Markov notation, the optimal decision at time \( t \) depends not only on the current state \( s_t \), but also on the history of the process, \( d_t = d^T_t(s_t, H_{t-1}) \) where \( H_t = (s_0, d_0, \ldots, s_{t-1}, d_{t-1}) \).

Despite this complexity, once an individual arrives at a state, the model retains the Markovian feature that the current optimal decision depends on process history only through its influence on the current state. Thus, the optimal decision depends only upon the current state \( s_t \); \( d_t = d_t(s_t) \).

We employ the notation \( X_{1Y2R} \) where \( X_1 \) and \( Y_2 \) represent the drugs taken in periods one and two, respectively, and R is the negative (N) or positive (Y) response in the associated period. Thus, \( B_{1N}A_{2P} \) means that Drug B was taken in period one with a negative response and drug A was taken in period two with a positive response. Therefore, estimating period three market penetration requires successive estimation and summation over the space including these 36 possible states for each drug. Period three probabilities are established as follows.

**Period Three Probabilities**

\[
P(A_1) = P(A_1|A_{1Y}A_{2P}) + \ldots + P(A_1|A_{1N}C_{2N}) + \ldots + P(A_1|B_{1N}A_{2P}) + \ldots + P(A_1|B_{1N}C_{2N}) + \ldots + P(A_1|C_{1P}A_{2P}) + \ldots + P(A_1|C_{1N}C_{2N})
\]

\[
P(B_1) = P(B_1|A_{1P}A_{2P}) + \ldots + P(B_1|A_{1N}C_{2N}) + \ldots + P(B_1|B_{1N}A_{2P}) + \ldots + P(B_1|B_{1N}C_{2N}) + \ldots + P(B_1|C_{1P}A_{2P}) + \ldots + P(B_1|C_{1N}C_{2N})
\]

\[
P(C_1) = P(C_1|A_{1P}A_{2P}) + \ldots + P(C_1|A_{1N}C_{2N}) + \ldots + P(C_1|B_{1N}A_{2P}) + \ldots + P(C_1|B_{1N}C_{2N}) + \ldots + P(C_1|C_{1P}A_{2P}) + \ldots + P(C_1|C_{1N}C_{2N})
\]

**Table 1 Postulated and estimated parameter values**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Postulated</th>
<th>Estimated</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response Time</td>
<td>.04</td>
<td>.013</td>
<td>.041</td>
</tr>
<tr>
<td>Recurrence Probability</td>
<td>.045</td>
<td>.042</td>
<td>.002</td>
</tr>
<tr>
<td>Response Probability</td>
<td>.05</td>
<td>.046</td>
<td>.001</td>
</tr>
<tr>
<td>Cost</td>
<td>-.03</td>
<td>-.029</td>
<td>.002</td>
</tr>
<tr>
<td>Delivery—nasal</td>
<td>-.01</td>
<td>-.006</td>
<td>.034</td>
</tr>
<tr>
<td>Delivery— injection</td>
<td>-.08</td>
<td>-.088</td>
<td>.040</td>
</tr>
</tbody>
</table>
Given our assumed parameters, random-utility maximization in period one leads to the following market shares:

\[
\begin{align*}
P(A_1) &= 47.3 \\
P(B_1) &= 21.3 \\
P(C_1) &= 31.3
\end{align*}
\]

After adjusting for the responses in period one migraine patients again choose a medication based on random-utility maximization.

**Probability of selecting A—period two (by response group)**

\[
\begin{align*}
P(A_2|A_{1Y}) &= 0.53 \\
P(A_2|A_{1N}) &= 0.10 \\
P(A_2|B_{1Y}) &= 0.42 \\
P(A_2|B_{1N}) &= 0.57 \\
P(A_2|C_{1Y}) &= 0.36 \\
P(A_2|C_{1N}) &= 0.63
\end{align*}
\]

**Probability of selecting B—period two (by response group)**

\[
\begin{align*}
P(B_2|A_{1Y}) &= 0.20 \\
P(B_2|A_{1N}) &= 0.36 \\
P(B_2|B_{1Y}) &= 0.30 \\
P(B_2|B_{1N}) &= 0.04 \\
P(B_2|C_{1Y}) &= 0.16 \\
P(B_2|C_{1N}) &= 0.28
\end{align*}
\]

**Probability of selecting C—period two (by response group)**

\[
\begin{align*}
P(C_2|A_{1Y}) &= 0.27 \\
P(C_2|A_{1N}) &= 0.53 \\
P(C_2|B_{1Y}) &= 0.27 \\
P(C_2|B_{1N}) &= 0.38 \\
P(C_2|C_{1Y}) &= 0.47 \\
P(C_2|C_{1N}) &= 0.08
\end{align*}
\]

Finally, using the period three probability formulas established earlier, it is possible to establish expected market penetration for drugs A, B, and C during period three; these penetration rates are 44%, 22%, and 33%, respectively.

These choice probabilities arise from a constructed learning rule. However, the rule does seem to generate somewhat realistic probabilities. Note that the probability of choosing a given drug in period two is always higher (lower) if the drug was successfully (unsuccessfully) employed in period one. Similarly, period three choice probabilities depend upon both decisions and outcomes in prior periods.

The model presented here represents decision-making by a set of primitives \((u, p, B)\). The utility function \(u(s, d_t)\) represents the agent’s preferences at time \(t\). The Markov transition probability \(p(s_{t+1}, d_{t+1})\) represents the agent’s subjective belief about uncertain future states. These agents behave according to an optimal decision rule \(d_t = d(s_t)\). Identification of \((u, p, d, B)\) depend upon data availability and what restrictions the analyst is willing to impose.

Here, we utilize general econometric and behavioral restrictions to draw on a number of powerful and well-accepted results from the extensive literature on estimation of static discrete-choice models [31]. This literature indicates that Equation 7, the mathematical representation of random utility decision-making, provides a reasonable approximation to observed behavior. Thus, we postulate the optimal decision rule \(d_t\) is maximization of expected utility. Employing multinomial logit estimation imposes this decision rule on either experimental or market data. This technique is readily available in most econometric software. In this example, we illustrate the advantages of collecting experimental data about preferences relating to a unique compound. Specifically, data collected from a choice-based survey like the instrument presented earlier allows recovering individual utility functions \((u_t)\) related to pharmaceutical compounds with unique attributes.

In this example, the subjective relief probability \((P_r)\) enters utility directly. Under the assumptions of constant utility parameters \((u)\) and decision rule \((d_t)\) represents the agent’s subjective belief about uncertain future states and is the only time variant factor influencing the Markov transition probability. In general, estimating such subjective beliefs is a difficult, data-intensive task [26]. However, because optimal decision-making depends heavily on \((P_r)\), inaccurately estimating this value will contaminate ultimate market share predictions. Therefore, correctly identifying the rule used for updating the success probability associated with each drug is critical.

### Table 2: Drug attribute profiles — New Pharmaceuticals

<table>
<thead>
<tr>
<th>Drug</th>
<th>Response Time</th>
<th>Recurrence Probability</th>
<th>Response Probability</th>
<th>Cost</th>
<th>Delivery Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.5 hours</td>
<td>15%</td>
<td>90%</td>
<td>$30</td>
<td>Oral</td>
</tr>
<tr>
<td>B</td>
<td>2 hours</td>
<td>30%</td>
<td>80%</td>
<td>$20</td>
<td>Nasal</td>
</tr>
<tr>
<td>C</td>
<td>2 hours</td>
<td>15%</td>
<td>70%</td>
<td>$10</td>
<td>Injectable</td>
</tr>
</tbody>
</table>

---

**Modeling Choice Behavior — New Pharmaceuticals**

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**Note that the probability of choosing a given drug**
In this work, we used a simple Bayesian updating scheme for illustrative purposes. Knowledge of the Bayesian updating scheme along with past decisions and outcomes allows determination of \((P_t)\) for each group.

Given the importance of \((P_t)\) in this model, it is natural to question how one might empirically estimate the function that gives rise to it. If one were to observe market behavior subsequent to estimating utility parameters from experimental data we need only apply the restriction that the decision rule takes the form of Equation 7. Doing so allows mathematical derivation of the subjective relief probabilities by observing market shares at each period in the following manner.

Assume that the period two market shares above are not forecast from a postulated updating rule. Rather, suppose these shares are observed and the updating rule is unknown. In this case, using the known drug profiles and estimated utility parameters presented earlier allows algebraic identification of the updated subjective response probability. For example, Drug A was selected by 47.3% in the first period. If Drug A were effective in the first period, patients update the response probability attribute. This updating results in a 53% market share for Drug A in period two for the group of patients who successfully employed Drug A in period one. Replacing the utility function for each drug with its calculated value allows solving for the updated Response Probability associated with Drug A. Because this group of patients has no personal experience with Drugs B and C, the expected utilities associated with these drugs are unchanged.

\[
\text{EU(Drug A)} = (.130)(1.5) - (.042)(15) + (.046)(\text{SRP}_A|A_{1Y}) - (.029)(30) + (1)(0) = ?
\]

\[
\text{EU(Drug B)} = (.130)(2) - (.042)(30) + (.046)(80) - (.029)(20) - (1)(.006) = 2.094
\]

\[
\text{EU(Drug C)} = (.130)(2) - (.042)(15) + (.046)(70) - (.029)(10) - (1)(.088) = 2.472
\]

The exponentiated utilities associated with each drug can be expressed as follows:

\[
e^{V_A|A_{1Y}} = e^{-1.305 + (.046)(\text{SRP}_A|A_{1Y})}
\]

\[
e^{V_B|A_{1Y}} = e^{2.094} = 8.117
\]

\[
e^{V_C|A_{1Y}} = e^{2.472} = 11.846
\]

And, using the following market share information from period two, Group A_{1Y}

\[
.53 = \frac{e^{V_{A}}}{e^{V_{A}} + e^{V_{B}} + e^{V_{C}}};
\]

\[
.30 = \frac{e^{V_{B}}}{e^{V_{A}} + e^{V_{B}} + e^{V_{C}}};
\]

\[
.47 = \frac{e^{V_{C}}}{e^{V_{A}} + e^{V_{B}} + e^{V_{C}}};
\]

it is straightforward to solve for the updated subjective response probability attribute algebraically yielding

\[
(\text{SRP}_A|A_{1Y}) = 95
\]

Subjective response probabilities for groups with different drug selection and response patterns can be identified in a similar fashion.

**Conclusion**

This paper presents a dynamic variation of a model often used to aid marketing decisions relating to conventional products. The model uses stated-preference data in a random-utility framework to predict adoption rates for new pharmaceutical products. The relevance of such a model for assessing...
real-world decisions depends critically on the empirical validity of the assumed random-utility functions. More realistic specifications require information on what drugs are included in the actual choice set, knowledge of perceptions regarding adverse and beneficial outcomes with their associated probabilities, and marginal rates of substitution among drug attributes and cost. Reliable preference information can arise from a suitable design, administration, and analysis of an SP survey [8]. This model focuses on patient preferences derived from an SP survey. However, even with an informed consumer, physicians still must act as agents for patients. If the consumer and physician assign different expected utilities to various drugs, the analyst is confronted with a principal-agent problem. This complexity can occur even if principals believe they are acting in the best interests of agents. The present work takes a first step toward examining demand. However, the dependence of the consumption decision on both patient and physician is not recognized in the model. Explicitly incorporating this important aspect of demand determination is a relevant avenue for future research.

In addition, this paper presents a Markov model of patient learning in drug selection. The simple learning rule presented here likely presents a rough approximation to reality. More closely approximating weighting rules used in real-world decision-making will improve demand forecasts. Better estimates of such rules can arise from analyzing additional SP survey data, market data, or a combination of these sources [32]. This model emphasizes the importance of learning and the influence of shifting preferences on market share. Thus, this research demonstrates both the strengths of stated-preference market research and its shortcomings for pharmaceutical applications. The integrated framework of random-utility and product attribute updating presented here is capable of accommodating a variety of pharmaceutical marketing and development problems. We have presented a model of how rational agents should behave under specified learning and decision rules. However, extending this framework could prove useful for the empirical evaluation of actual consumer behavior. Specifically, modeling stated-preference data gives insight into the form and parameters of the utility function underlying individual choice. Combined with market data, this information provides sufficient restrictions to allow model identification and estimation of the learning rule that governs attribute perceptions [26]. Thus, the union of experimental and market data holds strong promise for the variety of difficult pharmaceutical marketing problems that are complicated by learning, uncertainty, and choice.

The authors would like to thank William Desvousges and Larry Bell for helpful discussions. We also benefited greatly from the comments of three anonymous reviewers.

References

ADDENDUM

Please note the following correction: The abstract PGU15, on page 361 of Value in Health 3(5), entitled Costs and resources associated with the treatment of overactive bladder using retrospective medical care claims data, Williamson T, Hall J, Nelson M, Meyer J, should include the name Wagner S in the author listing.