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A Prelaunch Diffusion Model for Evaluating Market Defense Strategies

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This paper describes the development and application of a marketing model to help set an incumbent's defensive marketing strategy prior to a new competitor's launch. The management problem addressed is to assess the market share impact of a new entrant in the residential Australian long distance telephone call market and determine the factors that would influence its dynamics and ultimate market appeal.

The paper uses probability flow models to provide a framework to generate forecasts and assess the determinants of share loss. We develop models at two levels of complexity to give both simple, robust forecasts and more detailed diagnostic analysis of the effect of marketing actions. The models are calibrated prior to the new entrant's launch, enabling preemptive marketing strategies to be put in place by the defending company. The equilibrium level of consideration of the new entrant was driven by respondents' strength of relationship with the defender and inertia, while trial was more price-based. Continued use of the defender depends on both service factors and price. The rate at which share loss eventuates is negatively related to the defender's perceived responsiveness, saving money being the only reason to switch, and risk aversion.

Prelaunch model forecasts, validated six months after launch using both aggregate monthly sales data and detailed tracking surveys, are shown to closely follow the actual evolution of the market. The paper provides a closed-form multistate model of the new entrant's diffusion, a methodology for the prelaunch calibration of dynamic models in practice, and insights into defensive strategies for existing companies facing new entrants.

Key words: defensive strategy; brand choice; diffusion; forecasting
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Management Problem

Deregulation of long-distance telephone calls (toll calls) is occurring in many countries. Following the lead of the United States, Britain, Japan, Singapore, Australia, and many other governments have exposed their monopoly toll-call carriers to competition. More countries are following, e.g., Thailand, China, Latin America, and Eastern Europe (Beardsley et al. 2002). We describe the application of a marketing model to assist an existing company, Telstra, in defending its competitive position against Optus, the subsidiary of two large multinationals, which was about to enter its market.[1] In their home markets, the parents of the new entrant, Bell South and Cable & Wireless, were known for excellent customer service. The new entrant also enjoyed cost advantages over Telstra, at least in the short term, as a result of a regulatory decision. Optus was expected to attack Telstra on two fronts: better service and lower prices.

For Telstra, the defending company, the management problem was first to assess the likely impact of Optus on its share, and second to understand the determinants of customer switching so it could develop and test defensive strategies. The research objectives stemming from this management problem called for a dynamic model giving the new entrant's ultimate share and its evolution. These forecasts were required for network dimensioning, financial planning, and monitoring and control, as well as to enable management to test different marketing-mix strategies and environmental scenarios. Dynamic market defense is an important problem. A wide range of power, transport, and service monopolies once governed by regulation are being exposed to competition. Robertson and Gatignon (1991) point out that

[1] At the time of this application, Telstra was called Telecom Australia.

incumbents have an advantage over new entrants, but firms without a responsive defense strategy may forfeit that advantage.

We address the management problem of dynamic defense by first considering available modeling frameworks. After choosing a probabilistic flow approach, we derive two specific models to address the research objectives. The models are calibrated prior to launch, and their implications for preemptive management action described. Telstra also used the models for tracking postlaunch, and we provide the results of a forecast validation of the prelaunch model. We conclude with a discussion of how this application might be used to help other companies set defensive strategy over time.

In the application, we show how multistate dynamic models can be made to work in practice. The literature contains few real-world applications of dynamic models calibrated prelaunch (either from the new entrant's or defender's perspective). There are even fewer that are validated not just on postlaunch sales data but also on tracking the evolution of decision states. In developing our approach, we obtain a closed-form solution to a dynamic six-state decision model as well as comparing respondent-based information on rate parameter calibration to the use of analogy. Substantively, in looking at a new product from the defender's perspective, we consider a number of interesting managerial issues. Unlike postlaunch tracking tools that have been criticized because "after the fact, it's sort of like accident reports" (Dipasquale 2002), we provide managers with defensive tools when they are needed.

Available Modeling Approaches

Competitive strategy may be thought to consist of three components: understanding what competitors do, reviewing how incumbents can and do react to those actions, and calibrating marketplace response to both sets of behaviors. We focus on the third issue, prelaunch estimation of the pay-off matrix to the defender's and new entrant's possible marketing actions. This provides a critical input to any game-theoretic analysis of optimal competitive strategies, as well as management guidance. We start by reviewing existing calibration approaches in defensive marketing and the adoption of new products.

Market Defense

There is a growing body of descriptive research that examines the success of defensive strategies using historical and cross-sectional data (e.g., Ramaswamy et al. 1994, Gatignon et al. 1997). Such studies are valuable in identifying useful tools for the incumbent, but provide directional rather than quantitative estimates of optimal response to new entrants' actions. The normative stream of research provides analytical guidance to profit-maximizing strategies for defenders (e.g., Hauser and Shugan 1983, Kumar and Sudharsan 1988, Hauser and Gaskin 1984). However, this research looks only at comparative static equilibria, not at the dynamics of a new entrant's attack.

Models of New Product Acceptance

In the absence of specific response functions in the market defense literature to address particular management problems, we turn to the new product adoption literature for models of how much share a new entrant will get, how it will evolve over time, and its determinants.

Preference/Choice Models. The primary paradigm for determining the acceptance of a new product is utility theory, combined with discrete-choice theory (see Roberts and Lilien 1993, Table 2.6 for applications). Discrete-choice models show how product positioning (in terms of perceived attributes) may be translated into market share but rarely address how that share will change over time. Thus, they do not help with the market's evolution (see Roberts and Lilien 1993 for the few exceptions). For that, we turn to diffusion models.

Diffusion Models. In their most simple form, diffusion models have two components; a pool of future adopters, and a flow rate at which potential purchasers become adopters. Numerous extensions have been made to Bass' (1969) diffusion model, including the incorporation of marketing-mix elements and competition. Additionally, multistate diffusion models provide diagnostic guidance to the manager by including rejection, awareness, and repeat purchase (see Mahajan et al. 2001 for a review). While diffusion models provide insight into the dynamics of an innovation's sales, they do so from the perspective of the new entrant, not the incumbent. Additionally, they do not lend themselves easily to rigorous prelaunch calibration.

Probability Flow Models. A flexible modeling approach that captures both the explanatory power of discrete-choice models and the dynamics of diffusion models uses probability flow models. The framework consists of behavioral states through which consumers flow (e.g., awareness, trial, repeat), with the relative flow levels and rates from each state to all others being estimated. A specific type of flow model, semi-Markov models, allows flow in continuous rather than discrete time (Hauser and Wisniewski 1982a, b). Typically, Markov models are written in recursive form for computational purposes. The closed-form equivalent becomes complex when model parameters vary by observation period, but simplifies when, as in our detailed model, they are stable. In determining the number of behavioral states to include, there is a trade-off between the greater diagnostic information of a richer model and the cost and difficulty of estimating a more complex system. The ability to specify the behavioral states appropriate for a particular problem, together with the flow levels, flow rates, and their determinants, makes the framework appealing for the forecasting and marketing-mix allocation problem faced by defenders against a new entrant. Another advantage of these models is their suitability for monitoring and control purposes, given the detailed diagnostics they provide over time.

We draw on the probability flow approach for modeling consumer response to defensive strategy, the market defense literature to specify the appropriate marketing-mix elements, the utility/choice literature to provide a rigorous way to examine how these factors are likely to affect the flow levels between states, and diffusion models to specify the flow rates.

Model Development

The dynamic defense model is developed at two levels of complexity, following Urban and Karash's (1971) advocacy of evolutionary model building. First, we form a base model. Then, we expand the number of behavioral states to provide a more detailed view of the consumer. Both models are calibrated in three stages: specifying the behavioral states, estimating the relative flow levels in terms of management decision variables, and calculating the rate at which these flows will occur. Base model benefits include speed and ease of calibration (particularly prelaunch, when there is little marketplace information and consumers cannot provide detailed reactions to unfamiliar stimuli), robustness of forecasts, and ease of managerial interpretation. The advantage of the detailed model is a richness of diagnostic information, indicating managerial leverage points to influence consumer behavior.

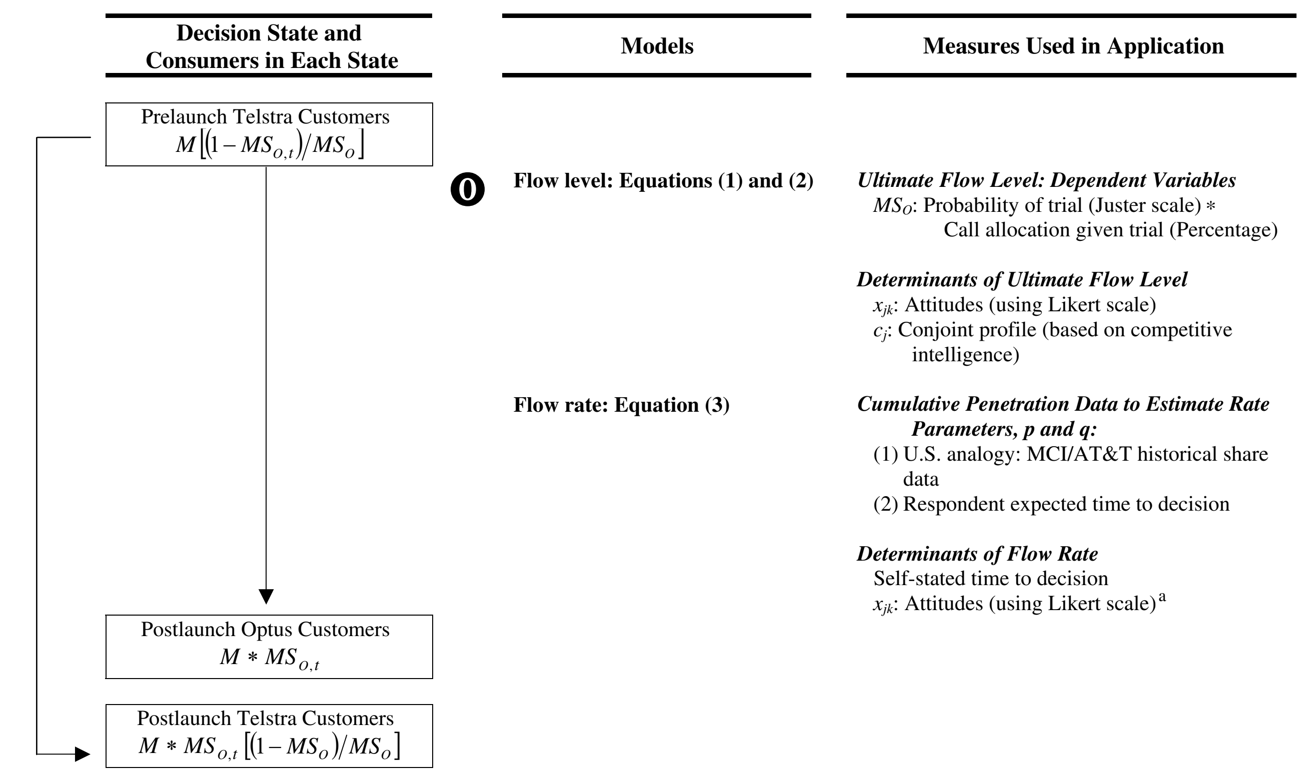
Base Model Specification

We use only three states in the base model: the initial state in which all customers belong to Telstra, and two captive states where customers either convert to Optus or remain with Telstra. All customers, M, start with Telstra. We assume that m will flow to the new entrant and $(M - m)$ will stay with Telstra (see Figure 1).

Specifying Flow Levels (⓿ in Figure 1)

Hauser and Wisniewski (1982a, p. 465) show that the logit model to estimate flow levels between states is a natural outcome of their assumptions. Using this

Figure 1 Relationship Between the Stages of Consumer Decision Making, Models, and Measures (Base Model)



[a] The determinants of flow levels and flow rates may be different variables. We refer to both as x_{jk} for the sake of parsimony.

formulation, Optus' share, MS_O, after diffusion is

$$MS_O = \frac{m}{M} = \left(\frac{e^{U_O - I}}{e^{U_O - I} + e^{U_T}}\right), \tag{1}$$

where U_O is the utility of Optus, U_T is the utility of Telstra, and I is the inertia or search cost associated with changing company.[2] By expressing these utilities in terms of their constituent perceived attributes, we can examine the effect of positioning and pricing on the equilibrium share of the new entrant, Optus (m/M):

$$U_j = \sum_{k=1}^{K} w_k x_{jk} - \lambda c_j \quad (\text{for } j = O, T), \tag{2}$$

where x_{jk} is the perceived level of attribute k of company j, w_k is the importance weight of attribute k (for $k = 1, 2, \ldots, K$), λ is the opportunity cost of money, and c_j is the price of company j's service.

In keeping with Urban and Hauser (1993, pp. 268–269), we allow for heterogeneity of perceptions, x_{jk}, but not tastes, w_k. However, in the application, different flow levels were calculated for four usage segments. The results are very similar when aggregated and for the sake of parsimony are not reported here.

Specifying Flow Rate. Citing extensive empirical evidence, Hauser and Wisniewski (1982a, p. 461) propose negative exponential or Erlang flow rates. We use the Bass model to specify the flow rate because it subsumes the negative exponential and, like the Erlang, allows maximum sales at a nonzero point in time. The flow rate parameters (p and q in Equation (3)) may be modeled in terms of their determinants.

Summary of the Base Model Formulation. The solution to the differential equation form of the Bass model after substituting m from Equation (1) is

$$\begin{aligned} MS_{O,t} &= \frac{m}{M}\left[\frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}\right] \\ &= \left[\frac{e^{U_O - I}}{e^{U_O - I} + e^{U_T}}\right]\left[\frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}\right], \end{aligned} \tag{3}$$

where $MS_{O,t}$ is the market share of Optus at any point in time, t. Note that by using a probability flow framework we achieve a model which, algebraically at least, subsumes two of the major traditions of new product modeling. If there are no dynamics, Equation (3) degenerates to a model analogous to a logit-type formulation. If m is given, then we have the Bass model.

[2] Note that the logit model provides the *probability* that an individual will flow into the adopting state. Equation (1) has been written as deterministic, whereas the logit model aggregated over the population gives the *distribution* of adopters. That is, the number of adopters will be stochastic because each individual's probability of adopting is a random variable. In practice, diffusion models tend to assume that the adopting population equals the *expected* number of adopters (the hazard rate times the market potential), a reasonable assumption for large populations (Jeuland 1979).

Detailed Model Specification

Telstra's objective was to reduce the rate of diffusion (p and q in Equation (3)) and to decrease the proportion of consumers who will ultimately switch (m/M in Equation (1)). We identify determinants of these in the base model. In the detailed model, illustrated in Figure 2, we move to three captive states, and insert two intermediate decision stages (consideration and trial). This detailed model has three flow rates: from susceptibility to consideration (or nonconsideration); from consideration to trial (or negative evaluation); and from trial to new entrant loyal (or brand switcher).

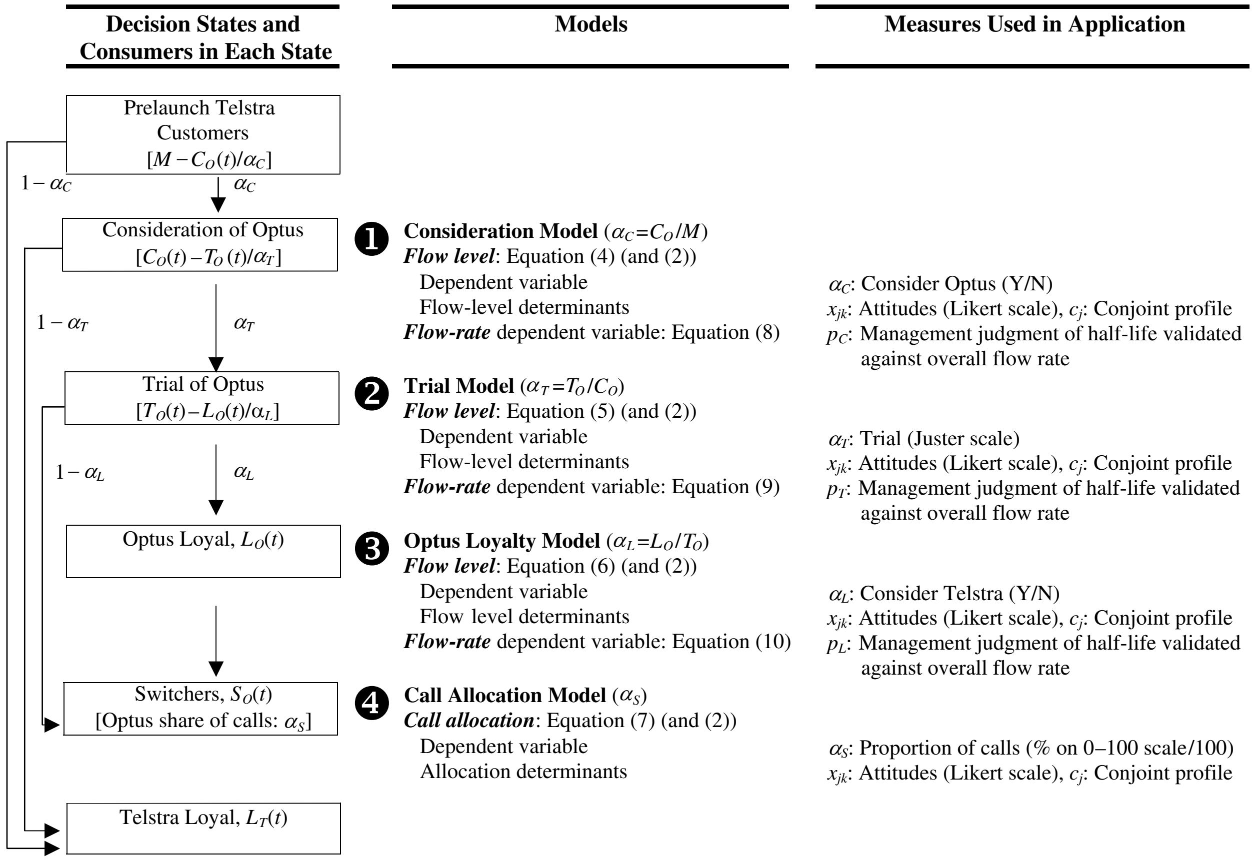
Specifying Behavioral States. Consideration is critical to the success of many new products. Roberts and Lattin (1991) estimate consideration levels for new product concepts ranging from 26% to 75%. Moreover, the determinants of consideration may be different from those of choice, offering the defender a number of stages at which it can stem the adoption tide. A proportion $\alpha_C = C_O/M$ of customers will ultimately consider Optus. The $M - C_O$ Telstra customers who do not consider Optus will stay loyal to Telstra (see Figure 2).

Trial has also been identified as a key element to the adoption of new products (e.g., Shocker and Hall 1986). Of those who consider Optus, many will not proceed to trial because the new entrant does not have sufficient utility advantage over the incumbent to overcome inertial forces. Therefore, a proportion $\alpha_T = T_O/C_O$, of Optus considerers will try and $(C_O - T_O)$ considerers will move to Telstra loyalty.

Triers may either become loyal to Optus or continue to use Telstra. A proportion, $\alpha_L = L_O/T_O$, of triers will become loyal to Optus, and $(T_O - L_O)$ triers will continue to use Telstra, allocating their calls between the two carriers. We could include more states (e.g., repeat before the loyalist decision) or flows (e.g., Telstra could use win-back strategies to regain Optus loyalists). However, for parsimony we limit the detailed model to the one in Figure 2.

Specifying Flow Levels. We need to specify the proportion of Telstra customers that will consider Optus, α_C; of considerers the share of Optus triers, α_T; and of Optus triers the proportion that will become Optus loyalists, α_L. Finally, for brand switchers, we need a call allocation model. Following Hauser and Wisniewski (1982a, p. 465), we use logit models for

Figure 2 Relationship Between the Stages of Consumer Decision Making, Models, and Measures (Detailed Model)



these flow levels. Algebraically, we represent the equilibrium flow levels below:

Proportion of Population Considering Optus, α_C (❶ in Figure 2):

$$\alpha_C = \frac{e^{CU_O}}{e^{CU_O} + e^{U_T^*}} = \frac{C_O}{M}, \tag{4}$$

where CU_O is the Optus consideration utility, and U_T^* is the benchmark utility against which it will be compared. Roberts and Lattin (1991, Equation (6)) provide an expression for the benchmark, U_T^*, in terms of Telstra's consideration utility and search costs.

Proportion of Considerers Trying Optus, α_T (❷ in Figure 2):

$$\alpha_T = \frac{e^{EU_O - I}}{e^{EU_O - I} + e^{EU_T}} = \frac{T_O}{C_O}, \tag{5}$$

where EU_O is Optus' and EU_T is Telstra's evaluation utility, and I represents search and inertia costs at trial.

Proportion of Triers Becoming Optus Loyal, α_L (❸ in Figure 2). Optus triers may continue to consider Telstra and alternate between the two companies, or become Optus loyalists. The proportion of Optus loyals, α_L, will be one minus the share of triers who still consider Telstra. This will be a function of the consideration utility of Telstra, CU_T, and some benchmark utility depending on inertia, search costs, and Optus' utility, U_O^*:

$$\alpha_L = 1 - \frac{e^{CU_T}}{e^{CU_T} + e^{U_O^*}} = \frac{e^{U_O^*}}{e^{CU_T} + e^{U_O^*}} = \frac{L_O}{T_O}. \tag{6}$$

Proportion of Calls That Switchers Allocate to Optus, α_S (❹ in Figure 2). For those who continue to use both carriers, we can model their relative usage as a function of the relative perceived utility of Optus and Telstra:

$$\alpha_S = \frac{e^{US_O}}{e^{US_O} + e^{US_T}}, \tag{7}$$

where US_O and US_T are switchers' utilities of Optus and Telstra, respectively, for specific calls. All of the consideration utilities (CU_O, U_T^*, CU_T, U_O^*), trial utilities (EU_O, EU_T), and call allocation utilities (US_O, US_T) may be expressed in terms of their multiattribute components (Equation (2)).

Specifying Flow Rates. For the detailed model, we assume negative exponential distributions for all flow rates. Fader et al. (2003) find that it fits and forecasts trial well for a variety of categories if a saturation constraint is imposed. Although it is not as general as the base Bass model, we use the simpler flow-rate model for parsimony.[3] We also assume that flow rates to different destinations from the same source are equal. Under the negative exponential flow-rate assumption, we specify the rates at which customers leave the prelaunch incumbent state (the consideration decision), Equation (8); the consideration state (the trial decision), Equation (9); and the trial state (the Optus loyalty decision), Equation (10); as follows:

$$\frac{dC_O(t)}{dt} = \alpha_C p_C (M - C_O(t)/\alpha_C) \quad \text{❶ in Figure 2,} \quad (8)$$

$$\frac{dT_O(t)}{dt} = \alpha_T p_T (C_O(t) - T_O(t)/\alpha_T) \quad \text{❷ in Figure 2,} \quad (9)$$

$$\frac{dL_O(t)}{dt} = \alpha_L p_L (T_O(t) - L_O(t)/\alpha_L) \quad \text{❸ in Figure 2,} \quad (10)$$

where p_C, p_T, and p_L, the flow-rate parameters, are constants. We could model these rates in terms of consumer attitudes (as with the base model), but for the sake of parsimony and because of the difficulty in calibrating such relationships prelaunch, we only look at rate determinants in the base model.

Summary of the Detailed Model

We can combine the flow levels represented by Equations (4) to (6) with the flow rates in Equations (8) to (10) to get a closed-form representation of the number of consumers in each state at any point in time. Combined with the call allocation of switchers (Equation (7)), this gives the market share of Optus at any point in time. Because utility is modeled as a function of constituent attributes and price, we can see how Telstra's and Optus' positioning will affect the diffusion process. The different determinants of flows at different decision stages allow us to identify where Telstra can best limit adoption of the new product.

Cumulative Level of Considerers at Time t, $C_O(t)$. To obtain the cumulative number of considerers, $C_O(t)$, we look at the proportion that has flowed from the Prelaunch Incumbent state in Figure 2 to Consideration. Equation (8) specifies how many people have flowed out of the Prelaunch Incumbent state, while Equation (4) determines how many of them flowed to Consider. Solving Equation (8) and setting initial conditions of $C_O(t) = 0$ at $t = 0$, we obtain

$$C_O(t) = \alpha_C M(1 - e^{-p_C t}). \quad (11)$$

Cumulative Level of Trial at Time t, $T_O(t)$. To obtain the cumulative number of triers, $T_O(t)$, we substitute $C_O(t)$ from Equation (11) into Equation (9). Solving the resultant differential equation in t, and setting initial conditions of $T_O(t) = 0$ at $t = 0$, gives cumulative trial, $T_O(t)$, in terms of time and the level and rate parameters, α_C, α_T, p_C, and p_T:

$$T_O(t) = \alpha_C \alpha_T M\left(1 - \frac{p_T}{p_T - p_C} e^{-p_C t} + \frac{p_C}{p_T - p_C} e^{-p_T t}\right). \quad (12)$$

Cumulative Level of Optus Loyalty at Time t, $L_O(t)$. Cumulative levels of Optus loyalty, $L_O(t)$, can also be estimated by substituting the expression for $T_O(t)$ from Equation (12) into Equation (10) and solving for $L_O(t)$, setting initial conditions of $L_O(t) = 0$ at $t = 0$:

$$\begin{aligned} L_O(t) = \Bigg[\alpha_C \alpha_T \alpha_L M\Bigg(1 &- \frac{p_T p_L}{(p_L - p_C)(p_T - p_C)} e^{-p_C t} \\ &+ \frac{p_C p_L}{(p_L - p_T)(p_T - p_C)} e^{-p_T t} \\ &- \frac{p_C p_T}{(p_L - p_C)(p_L - p_T)} e^{-p_L t}\Bigg)\Bigg]. \end{aligned} \quad (13)$$

Membership of Other States at Time t. Because a proportion $(1 - \alpha_L)$ of Optus triers become switchers (see Figure 2), the number of switchers at time t, $S_O(t)$, is given by

$$S_O(t) = (1 - \alpha_L)/\alpha_L * L_O(t). \quad (14)$$

The number of Telstra loyals at time t, $L_T(t)$, nonconsiderers plus nontriers, is

$$L_T(t) = (1 - \alpha_C)/\alpha_C * C_O(t) + (1 - \alpha_T)/\alpha_T * T_O(t). \quad (15)$$

Optus' share, $MS_O(t)$, at any point in time is the proportion of the population that is Optus Loyal ($L_O(t)$) plus the proportion of switchers ($S_O(t)$) times the proportion of their calls that are going to Optus (α_S):

$$MS_O(t) = L_O(t) + S_O(t) * \alpha_S. \quad (16)$$

Thus, the model gives us a closed-form expression of the number of people in each state in terms of time t; flow levels α_C, α_T, and α_L; and flow rates, p_C, p_T, and p_L. Because we can express α_C, α_T, α_L, and α_S in terms of their determinants in Equations (4) to (7), management also has a good idea as to how to influence flow levels between states (and in principle the flow rates: p_C, p_T, and p_L).

In formulating the model we make a number of trade-offs. Comparing our detailed model to ASSESSOR (Silk and Urban 1978), we see first that the original ASSESSOR paper does not model sales dynamics. It only examines equilibrium shares

[3] One reason for including the coefficient of internal influence, q, in the Bass model is to allow it to track S-shaped diffusion patterns. The use of a multistate flow model achieves the same purpose.

(although some subsequent applications have estimated dynamics). ASSESSOR includes many of the same stages (consideration, trial, purchase allocation, etc.), but by using two different models. To gain correspondence between its models, the authors make some assumptions more likely to hold with packaged goods than with telecommunications (e.g., "consideration and trial are operationally similar"). Also, the original ASSESSOR paper does not measure the determinants of consideration, trial, and repeat that are important in this application. Within our multistate approach, the use of discrete-choice models for flow levels and diffusion models for flow rates subsumes examples of a large number of other models (hazard rate, conjoint analysis, etc.). The base model provides some insurance against the dangers of increased complexity associated with the detailed model.

Applying the Model

We develop a methodology to calibrate the model prior to launch. Calibration has five components: elicitation of the drivers of utility (the attitudinal items in Equation (2)), identification of the target market and sample selection, design of concept stimuli to represent the Optus service offering and possible Telstra responses to it, development of measures to calibrate respondents' reactions to the new concept, and estimation.

Identification of Drivers of Utility

With Telstra's senior management, we identified the range of strategic options available to Optus and possible responses by Telstra, including possible service features and different pricing levels and formats. Next, 17 customer focus groups were held to explore the decision-making process, including key factors that would influence switching: attitudes to the incumbent, expectations of the new entrant, and inertial and search cost factors. Focus groups were conducted in three state capitals and two rural areas by a professional market research firm, with participants screened on the basis of call usage.

Sample Selection

Telstra provided a list of possible respondents, segmented by call usage, based on its internal company records. We used systematic sampling on this sampling frame to select 1,200 respondents yielding 801 completed, usable interviews. Information was collected in 45-minute face-to-face interviews conducted at the respondent's residence. Field research was conducted approximately three months prior to the Optus launch and results from calibrating both the base model and detailed model were made available to Telstra senior management one month before launch.

Design of Concept Stimuli

Telstra devoted considerable resources to understanding the positioning that Optus would seek and how it would be priced. For example, job vacancy advertisements of Optus described the sort of company that it was going to be. The press contained articles in which Optus management discussed its objectives. Finally, a lot was known about how Bell South and Cable & Wireless behaved in their home and foreign markets. Based on this information, Telstra commissioned its advertising agency to develop a series of advertisements to simulate how Optus might communicate. Optus had also released some information about its plans for pricing. After evaluating the likely positioning and marketing mix of Optus, Telstra developed possible pricing plans and service initiatives to blunt the impact of the Optus campaign. Respondents were exposed to two stimuli regarding Optus. The first was a detailed description of its service offerings and position, designed to simulate full information evaluation of the service, after which consideration was gauged. Service levels were described by sound quality, availability, billing format, charging method, and customer service and complaint handling. The second stimulus was a series of pricing scenarios, after which trial intent, call allocation, and continued Telstra consideration were measured. The conjoint price analysis consisted of a full factorial of six price levels (with Optus discounts from −5% to +20% of Telstra's price in 5% gradations) combined with four price-discount plan scenarios (Optus only, Telstra only, both, neither). Discount plans were specified in terms of cost of plan, time of savings, level of savings, geographic coverage of savings, phone numbers covered, and minimum thresholds. Respondents saw four pricing plans each. These two sets of materials allowed stimuli that reflected how the market would evolve from a supply perspective. This application is consistent with the criteria that Wittink and Bergestuen (2001) suggest as those under which conjoint analysis is likely to perform well (incremental innovation, weighting by usage, few attributes, etc.).

Measures

We used standard validated measures to calibrate consumers' reactions to the new product stimuli. The base model in Equations (1) and (3) requires estimates of the flow level to Optus (m/M) and the flow rates (p and q) to establish the dynamics of Optus' share over time. Additionally, we need to determine how the marketing activities of Telstra (and Optus) would affect the flow level and its rate (Equation (2)). To estimate these equations, we required measures of the ultimate probability of adoption, rate parameters, the two competitors' pricing, and consumer attitudes to their service levels.

Attitude items were measured after exposure to the Optus offering on a five-point Likert scale. We used 14 items for Telstra's performance relative to Optus' expected performance, and 9 items for respondents' attitudes to the difficulty and cost of changing. Probability of switching was gauged by the probability of Optus trial, times the call allocation to Optus, given trial. Utility was not measured directly, but imputed from the logit model. Rate parameters for the base model were estimated in two ways. We asked respondents how long they thought it would take them to make a decision and act on a possible change of long-distance provider. To obtain some convergent validity, we used sales dynamics from a similar launch in an overseas market. U.S. market share data were available on a quarterly basis from the Federal Communications Commission (1990), giving early market share gains of MCI, the first entrant against AT&T. This gave us a maximally different second estimate of the rate parameters.

In the detailed model, prelaunch measures for the dependent variables in the flow-level models (Equations (4) to (7)), were operationalized as follows. Optus consideration (yes/no on a bipolar scale) was measured after exposure to the service offering. Probability of trial (on an 11-point Juster scale), continued consideration of Telstra (yes/no on a bipolar scale), and likely call allocation between Optus and Telstra for switchers (as a percentage) were collected after each of the four pricing scenarios. Calibration of the flow rates between states in the detailed model is somewhat more difficult prelaunch. Data on the evolution of consideration, trial, and new-entrant loyalty in the analogous overseas market were not available. While we asked respondents about their overall expected decision times, we did not think they could give reliable answers to questions about the time to consider, the time from considering to trial, and the time when their behavior would stabilize. We had consumer judgment of the overall rate, as outlined in the base model description. We divided it into its component flows by using a decision calculus approach, combining management's judgment with the experience of their market research agency (Little 1970). Because the rate parameters are not intuitive to managers, we asked the Telstra project team to estimate the time it would take half of the population to flow out of a state after entering it. We pooled the resultant estimates by averaging.

In summary, all data to calibrate both models are based on consumer feedback from the market research with two exceptions. First, we use an analogous market to provide convergent validity of the rate parameters in the base model. Second, we use management judgment to allocate the overall respondent-sourced rate parameter into component flows between the different states.

Estimation

Estimating both the base model and the detailed model involve calculating flow levels and flow rates. We estimate these rates separately. Levels and rates are separable in the base model (Equation (3)), so the results will be the same as for a one-step estimator. For the detailed model, we use separate estimation to simplify calibration. Before estimating the models, we study the structure of respondent attitudes using principal components factor analysis using Statistica software (de Sa 2003). The logit models of flow levels and call allocation (Equations (1), (2), and (4)–(7)) relating the probabilities to the attitudinal factors and price were estimated using a maximum-likelihood estimation program, BLOGIT. Rate parameters (Equations (3), (8), (9), and (10)) were estimated using the nonlinear least-squares routine in Statistica.

Results

The Structure and Level of Customer Attitudes

Prelaunch calibration proceeds by studying the structure of respondent attitudes to Telstra relative to Optus, and search and inertia. These attitudes, together with pricing plans, provide the determinants of flow levels to Optus and, in the base model, the flow rate at which it will be realized. We reduced the 23 attitude items using a principal-components factor analysis. Based on a scree test, eigenvalues, and interpretability, we used three factors to describe how respondents felt about Telstra relative to Optus, and four to embody attitudes to competition, inertia, and search costs. After Varimax rotation, the three factors underlying Telstra attitudes relative to Optus were called "strength of relationship," "service delivery," and "big and impersonal." The four factors relating to switching were "no downside," "restlessness," "high inertia," and "competition irrelevant." Average item levels are valuable in their own right. Telstra was perceived as responsive to customers' needs and easy to contact. However, respondents believed that most people had a complaint about Telstra. With respect to the inertial/search cost items, on the positive side most people had high information uncertainty and felt that Optus would not have a complete range. On the negative side, they welcomed competition and perceived Optus as low risk.

Estimating the Base Model, Prelaunch

The base model has two parts: flow levels (the number of people who will ultimately adopt Optus) and flow rates (how quickly adoption will occur). For both, we estimate their expected value under the most likely marketing scenario ("the standard defense plan"), and then we examine their determinants.

Table 1 Base Logit Model Estimated Prelaunch (Equation (1)), ❶ in Figure 1

Variable	Including defensive variables: Parameter value	Including defensive variables: Standard error	Entrant's marketing mix only: Parameter value	Entrant's marketing mix only: Standard error
Constant	−0.33	0.07	−0.33	0.07
Price of Telstra − price of Optus, P	0.75	0.04	0.74	0.04
(Price of Telstra − price of Optus)^2, P^2	−0.23	0.05	−0.23	0.05
Optus price plan, δ_0	0.20	0.05	0.19	0.05
Telstra price plan, δ_T	−0.16	0.04		
Strength of relationship, X_{1T}	−0.11	0.09		
No downside, X_{1S}	0.32	0.09	0.32	0.09
Restlessness, X_{2S}	0.39	0.09	0.42	0.08
High inertia, X_{3S}	−0.24	0.08	−0.25	0.08
Model fit	$L(0)$: −2,216, $L(B)$: −1,789, $\chi^2_9 = 848$		$L(0)$: −2,216, $L(B)$: −1,803, $\chi^2_7 = 828$	
Test for difference between models	$\chi^2_2 = 20$, $p < 0.001$			

Ultimate Flow Level to Optus and Its Determinants. Based on the standard defense-plan scenario (provided to respondents in the concept description), respondents provided the chances of eventually switching to Optus. The average of these probabilities (after reweighting for bill size) was 21.9% if Telstra could achieve perceived price parity and 32.7% if Optus was perceived as being 5% cheaper on average. As nonlinear effects of price would have important managerial implications for Telstra, we incorporated a quadratic price term in the base flow-level model (Equations (1) and (2), flow level ❶ in Figure 1).

Table 1 shows that one relative performance factor (X_{1T}) and three inertial/search cost factors (X_{1S}, X_{2S}, X_{3S}) are significant in determining share loss.[4] Relative price is significant and nonlinear, suggesting that decreasing perceived relative price will have a positive but diminishing return on share. Pricing plans were significant for both players, with unequal effects. Optus benefits more from pricing plans than Telstra. Few diffusion models include the marketing mix of the defender as well as that of the innovator. For the sake of comparability, we estimated our logit model with only the new entrant's pricing and inertial variables. In Table 1 we see a significant loss of fit according to a χ^2 test, as well as a loss in the ability to gauge the effects of Telstra's different strategies. The direct effects of Telstra's defense (both price and strength of relationship) were important, but there is some indication that indirect effects were also extremely relevant. The degree of inertia that respondents felt depended very much on Telstra's perceived performance. For example, a regression of "restlessness" (X_{2S}) shows a significant relation with attitudes of Telstra being "big and impersonal" ($t = 7.11$), having high "service delivery" ($t = -6.37$), and a "strong relationship" (X_{1T}) ($t = -10.82$). $\bar{R}^2$ was 0.20 on individual-level data.

Flow Rate to Optus and Its Determinants. Having estimated the determinants of Optus adoption, we consider how quickly it will be realized. Using seven years of quarterly U.S. data from the launch of MCI, we estimated rate parameters in the Bass model using nonlinear least squares. In Table 2 we show results for the Bass model with $q = 0$, as q was not significant when estimated for the analogous market (or self-stated decision times), and the comparison of the constrained and unconstrained models shows no loss when q is constrained. The nonsignificant q is not surprising given the large amount of publicity (external influence) associated with the launch of a second telephone network, and is consistent with the postlaunch finding of Hauser and Wisniewski (1982b, p. 165) with respect to a new public transit system. These results suggest that in the analogous market, saturation occurred with MCI gaining 44% of AT&T's calls in a duopoly, and a highly significant coefficient of external influence, p, of 0.057.

Using five different time ranges, we asked respondents how long they would require to evaluate Optus. That gave us the number of customers who would have made their decision at five different points in time. Because all callers will eventually reach a decision, we set $m/M = 1$ and estimated p from these self-stated decision times.[5] See Table 2 for the results of fitting the Bass model, with $q = 0$, to these data. Again

[4] Variable selection was performed by stepwise elimination here and for the detailed model. This gave the same result as fitting the full models and eliminating all nonsignificant variables. Ideally, historical call data would have been used for convergent validity, but they provide category, rather than brand price, elasticities.

[5] While all respondents will eventually reach a decision, to test the robustness of our rate data we estimated m/M as well. m/M comes out to be 0.8, which is not statistically different from 1 given the few degrees of freedom.

Table 2 Base Model Flow Rate: Estimation of Bass Model, with $q = 0$, ❶ in Figure 1

	Analogous market		Self-stated decision times	
	Parameter estimate	Standard error	Parameter estimate	Standard error
m	0.439	0.010	1.000	—
p	0.057	0.003	0.063	0.007
q	0.000	—	0.000	—
R^2 adjusted	0.973		0.972	
n (observations)	28		5	

the coefficient of external influence, p, is strongly significant (despite the low power), and the fit is good (even adjusted for degrees of freedom). Based on these two independent analyses, we averaged the estimates of p (0.057 and 0.063), giving an estimate of the external influence rate of 0.060.

Measuring the time respondents think it will take to reach a decision enables us to estimate the rate parameter prelaunch, based on the feedback from the target population itself. Additionally, however, we can model the factors associated with fast and slow decision making. While the primary challenge to the defender is to reduce its share of calls lost, the secondary challenge is to slow that rate. We examine the determinants of a high flow rate by regressing the time to decision on the attitude items. (See Table 3 for these results.) A short time to adoption is associated with negative relative attitudes towards Telstra (e.g., "not responsive to my needs") and a slow rate to unfavorable attitudes towards competition and inertia (e.g., "using Optus would be risky").[6]

Summary of Base Model. Combining the base flow level with the base flow-rate model, the overall model from Equation (3) is

$$MS_{O,t} = \left(\frac{1}{1+e^{(U_T-U_O)+C}}\right)(1-e^{-0.060t}), \qquad (17)$$

where

$$U_O - U_T = 0.751P - 0.230P^2 - 0.160\delta_T + 0.197\delta_O - 0.110X_{1T},$$
$$-C = -0.327 + 0.320X_{1S} + 0.385X_{2S} - 0.244X_{3S}$$

(variables as defined in Table 1).

Equation (17) was used to generate forecasts under the standard defense-plan scenario, to evaluate the effect of possible Optus pricing and service initiatives, and to test possible Telstra defensive reactions.

[6] An alternative and preferable approach would have been to model the hazard rate, p, as $p = p(x)$. In the actual application we modeled time to adoption, and so that is what is reported here.

Table 3 Base Model—Prelaunch Relationship Between Flow Rate (Measured by Expected Time to Adoption) and Inertial Variables (Regression Model)

Variable	Parameter value	Standard error
Constant	2.01	0.26
Telstra is not responsive to my needs	−0.12	0.04
I would use Optus to teach Telstra a lesson	−0.08	0.04
Saving money would be the only reason to use Optus	0.10	0.04
Using Optus might be risky	0.20	0.05
n (number of respondents)	434	
R^2 adjusted	0.10	
$F_{5,428}$	11.18, $p < 0.001$	

Estimating the Detailed Model, Prelaunch

Calibrating the detailed model involved estimating the three flow levels and flow rates through the states of the model: to consideration, to trial, and to Optus loyalty; and deriving the call allocation for those who continued to switch between the two companies in equilibrium.

Flow Levels in the Detailed Model and Their Determinants. Using the standard defense-plan scenario, under full information 71% of respondents said that they would consider Optus. The average probability of trial was 0.50 (T_O in Figure 2). After trial, 27% of the population stated that they would continue to use Telstra for some calls, while 23%, L_O, expected to become loyal to Optus. Switchers gave the percentage of calls that they expected to make with Optus as 23%. Using Equation (16), Optus' ultimate share was forecast to be 29%, assuming a 3.3% perceived Optus price advantage. Although we use different estimation and formulations, both the base and detailed models are based on feedback from the same respondents. Therefore, it is not surprising that they give similar estimates.

To examine the determinants of the equilibrium shares in the detailed model, we estimated the four logit models: consideration, trial, Optus loyalty, and call allocation for switchers (Table 4).

Consideration of Optus (*Equation* (4)) was a function of the relative strength of the relationship with Telstra, as well as three inertial variables (no downside, restlessness, and high inertia).

Trial (*Equation* (5)) was estimated with attitudinal factors to Telstra and Optus, as well as price (in a nonlinear form) and pricing plans. While Telstra's relative performance was significant in preempting consideration of Optus, it was no longer significant at the trial stage. The only significant nonprice attribute was how "restless" the respondent was. Perceived price was significant, as were pricing plans providing discounts in different formats. This suggests that once

Table 4 Detailed Model: Prelaunch Calibration Equilibrium Flow Logit Models

(A) Consideration Model: "I would consider Optus" (Yes/No), ❶ in Figure 2

Variable	Parameter value	Standard error
Constant	0.70	0.08
Strength of relationship, X_{1T}	−0.14	0.09
Service delivery, X_{2T}	−0.11	0.09
No downside, X_{1S}	0.53	0.09
Restlessness, X_{2S}	0.84	0.10
High inertia, X_{3S}	−0.29	0.09

Notes. $L(0)$: −555, $L(B)$: −444, $\chi^2_6 = 222$, $p < 0.001$.

(B) Trial Model: "I would try Optus" (11-point Juster scale), ❷ in Figure 2

Variable	Parameter value	Standard error
Constant	0.73	0.09
Price of Telstra – price of Optus, P	0.77	0.05
(Price of Telstra – price of Optus)^2, P^2	−0.26	0.06
Optus price plan, δ_0	0.17	0.06
Telstra price plan, δ_T	−0.16	0.05
Restlessness, X_{2S}	0.27	0.10

Notes. $L(0)$: −1,417, $L(B)$: −1,218, $\chi^2_6 = 398$, $p < 0.001$.

(C) Optus Loyalty: "I would not continue to use Telstra" (Yes/No), ❸ in Figure 2

Variable	Parameter value	Standard error
Constant	−0.41	0.09
Price of Telstra – price of Optus, P	0.63	0.06
(Price of Telstra – price of Optus)^2, P^2	−0.10	0.07
Optus price plan, δ_0	0.27	0.06
Telstra price plan, δ_T	−0.13	0.06
Big and impersonal, X_{3T}	0.32	0.11
No downside, X_{1S}	0.25	0.13
High inertia, X_{3S}	−0.32	0.11
Competition irrelevant, X_{4S}	−0.17	0.11

Notes. $L(0)$: −1,126, $L(B)$: −978, $\chi^2_9 = 296$, $p < 0.001$.

(D) Call Allocation to Optus for Switchers (Percentage), ❹ in Figure 2

Variable	Parameter value	Standard error
Constant	1.03	0.10
Price of Telstra – price of Optus, P	0.50	0.06
(Price of Telstra – price of Optus)^2, P^2	−0.13	0.07
Optus price plan, δ_0	0.25	0.06
Telstra price plan, δ_T	−0.12	0.06
Big and impersonal, X_{3T}	0.16	0.11
No downside, X_{1S}	0.16	0.13
High inertia, X_{3S}	−0.23	0.12

Notes. $L(0)$: −1,126, $L(B)$: −935, $\chi^2_8 = 382$, $p < 0.001$.

Optus was considered, the battleground would move more towards price. As with the base model, price is significant in a nonlinear way.

Optus Loyalty (*Equation* (6)) was related to price, attitudes of Telstra relative to Optus, and inertial variables. Optus' price plans are more effective than Telstra's, suggesting that if trial is achieved, price plans represent a valuable offensive marketing tool for Optus, but provide less protection for Telstra if it matches them. An attitude of Telstra being "big and impersonal" increases the chances of consumers ceasing to use Telstra, as does a belief that there is "no downside" to Optus. "High inertia" (or habit) is likely to assist Telstra in staying in the consideration set. (At the time, callers had to dial an extra digit to use Optus.) Those for whom "competition was irrelevant" are also likely to continue to use Telstra.

Call Allocation Model (*Equation* (7)). The relative allocation of calls for switchers was modeled using a logit model on price and attitudinal factors. Price was the most significant determinant in call allocation, followed by the availability of pricing plans. If a consumer has pricing plans from both companies, an Optus pricing plan will be more effective in gaining share than a Telstra plan will be in stopping it. Factors that affected Optus' call allocation amongst switchers were whether Telstra was disliked (seen as "big and impersonal" relative to Optus) and whether there was "no downside" to using the competition (in terms of financial or psychological cost). "Inertia" still continues to favor Telstra.

Flow Rates in the Detailed Model. Consumers received their bills on a monthly billing cycle. As outlined in the measurement section, we asked management and the market research agency to estimate how many bills consumers would receive before they considered, tried, and stabilized their behavior with respect to Optus. Receipt of a bill was seen as an important stimulus because it was at this time that potential switchers could compare what Optus' and Telstra's price structures meant for them personally. Telstra had been tracking consumers' awareness and consideration ever since newspaper articles had foreshadowed the Optus launch, a period of approximately 12 months. These data suggested that approximately three months would be the median time to gain consideration. Accordingly, the rate of flow into consideration, p_C, was set equal to 0.231, corresponding to 50% of callers making the consideration decision within three billing cycles. The rate at which trial was realized was estimated by management judgment to have a median of two billing cycles, ($p_T = 0.347$) somewhat shorter than consideration. For Optus loyalty, the rate of conversion was expected to be slow because, unlike trial, there are significant long-term ramifications for the customer.

Management estimated that 50% of the Optus users would decide whether to continue to use Telstra within 3.5 billing cycles ($p_L = 0.198$). The convolution of these management judgments was then compared to the overall flow rate, based on respondent data and market analogy.

Although the base and detailed models have slightly different time trajectories, we can compare their average growth rates. If we compound the detailed model flow rates and estimate the result with the negative exponential rate of the base model, we obtain an estimate of p, the rate parameter, of 0.062, showing close correspondence to the base model rate parameter of 0.060 (from an analogous market and respondents' self-reports). While we rely on management judgment for the allocation of rates between states, we can be more comfortable with the overall rate that these flows imply.

Overall Detailed Model. The logit models in Table 4 and the flow rates calibrated above can be substituted in Equations (4)–(7) and (11)–(16), respectively, to give a closed-form representation of the number of consumers in any state at any time analogously to Equation (17) for the base model. (It has not been included simply in the interests of preserving journal space, because it is both straightforward and cumbersome.)

Management Implications and Extensions

The detailed model identifies the drivers of consideration, trial, Optus loyalty, and call allocation, under control of both Telstra and Optus. It was provided to Telstra top management in the form of workshops and a report. It was delivered to Telstra marketing analysts and strategists as a PC-based decision-support aid that enabled them to simulate the effect of Optus initiatives and Telstra responses to blunt their effect. To reduce Optus' equilibrium appeal, Telstra can improve attitudes towards it (e.g., the strength of its customer relationships) or increase the cost of search (e.g., stress the possible downside involved in switching). (See Table 1.) Attitude levels were very diagnostic for Telstra. Telstra's perceived responsiveness and ability to be contacted obviated the need for a planned customer contact point campaign. However, beliefs about Telstra service (and its effect on switching levels in Tables 1 and 4) led to a major service-level communication program. One of the study's key findings was that improving attitudes to its service would give Telstra indirect benefits from increasing inertia as well as direct effects. To slow its rate of share loss, Telstra can appear more responsive and emphasize that saving money is not the only important attribute in switching now (see Table 3). Based on these findings, Telstra instituted a micro service delivery program at the customer interface. In particular, billing received special attention. 59% of the population believed that "most people had a billing problem with Telstra," while less than 19% reported having personally experienced one. This suggests that beliefs about service quality were at least as large a problem as the physical delivery of service. As well as focusing management actions, the model was also used extensively for forecasting purposes.

In addition to the insights gained from applying the base and detailed models, the flexibility of the logit choice framework, combined with negative exponential flow between states, allowed it to be extended in a number of ways. These included the incorporation of different price effects, segmentation, and evaluation of growth in category volume. Postlaunch, the price variable was refined by including a "don't know" category. "Don't knows" (25% of the tracking sample) had the same probability of choosing Telstra as those who believed that Telstra was 10% cheaper than Optus (less than 1% of the sample). Based on this, Telstra aimed for price comparability rather than price equality or superiority. The desired answer to "Who is cheaper?" was not "Telstra" (a position that was hard to sustain), but "It depends." Telstra needed to ensure that there were always some routes and times of day when it was cheaper than Optus. With respect to segmentation, fees for pricing plans were also tested in the conjoint model. Fees have the advantage that they made pricing plans relatively less appealing to the "valuable, not vulnerables," thereby not giving away margin to customers who had a low probability of choosing Optus. That is, those who were considering switching were more engaged in information search, more likely to calculate the net benefit of a plan, and hence would realize that it had a net benefit. Those less likely to switch were unlikely to calculate the net benefits of a price plan, and so would avoid paying extra for it, given its uncertain benefits. Finally, the model was extended to examine category growth. Using a nested logit framework, the inclusive value of having an extra provider was calculated and the category growth from having two companies, with their greater geographic coverage, lower prices, and increased marketing activity, was estimated. While the growth in the category somewhat mitigated the negative effects of a price war, it did not change any of the implications for defensive strategy from the share analysis described here.

Validation

Telstra share loss was followed by senior management on a weekly and monthly basis, using both sales results and the tracking study. Six months after the Optus launch, Telstra management requested the updating of the model to refine its defensive marketing mix. This enabled us to validate the prelaunch forecasts. Pricing and marketing-mix variables were all very close to prelaunch assumptions (reflecting Telstra's excellent prelaunch intelligence). Results of the forecast validation are in Table 5.

The base model fit well (with mean absolute percentage error, MAPE, of 14.8%). The detailed model, while reasonably accurate on an overall basis, reveals some interesting divergences between marketplace reality and our forecasts. Consideration and trial were higher than we forecast, but this was compensated for by a decrease in Optus loyalty. One cause for this could be the high initial expectations set by Optus. Another reason, which became clear in postlaunch tracking, was inertia. We expected inertia to be a strong influence in discouraging consideration, but it was more of an influence in gaining continued usage of Telstra (see Tables 4A and 4C). Based on the calibration of the prelaunch model, we believed that preempting trial was the strongest line of defense for Telstra. While undoubtedly it was the major line of defense (trial was only 27% after six months), the habit of dialing Telstra for toll calls was so strong that even after using Optus, there was still a very strong tendency to use Telstra for most calls.

Table 5 **Forecast Evaluation: Accuracy of Base and Detailed Models (Calibrated Prelaunch)**

(A) Base Model: Optus Share Trajectory Over Time

Month	Actual (%)	Forecast (%)	Forecast error (%)	MAPE (%)
1	1.1	1.7	+0.6	54.5
2	3.1	3.3	+0.2	6.5
3	4.0	4.8	+0.8	20.0
4	6.1	6.2	+0.1	1.6
5	8.0	7.5	−0.5	6.3
6	8.8	8.8	0.0	0.0
Mean absolute percentage error (MAPE)			+0.37	14.8

(B) Detailed Model: Optus Share by Decision State at Month 6

Decision state	Actual (%)	Forecast (%)	Forecast error (%)	MAPE (%)
Consideration, $C_0(t)$	54	52.9	−1.1	2.0
Trial, $T_0(t)$	27	25.1	−1.9	7.0
Switcher share, $(S_0(t) * \alpha_S)$	5	4.7	−0.3	6.0
Optus loyalty, $L_0(t)$	4	4.3	0.3	7.5
Overall share, $MS_0(t)$	8.8	8.9	−0.1	1.1

Note. Forecasts and actuals are disguised by the same absolute share percentage.

The model was updated by reestimating the logit models and rate parameters. As anticipated, the logit flow-level models proved to be reasonably stable. Discrete-choice theory and conjoint analysis are robust methods of estimating new product share prior to launch. However, the use of prelaunch survey data to estimate the rate of diffusion is less well established. Conversely, in contrast to survey data, early sales data tell us less about the value of m/M than they do about diffusion rates (see Heeler and Hustad 1980). There was a high level of uncertainty in our prelaunch calibration of flow rates (particularly by decision state), so we wanted to validate these after consumers had firsthand experience with Optus. Postlaunch, we could do this by using early sales data and the monthly tracking study. Sales data enabled us to fit the base model (imposing a value of m/M from the base logit model) to test the accuracy of our prelaunch rate estimates of p and q. Using six months data, and putting m/M equal to 0.29 from the prelaunch logit model, gave a similar fit ($\bar{R}^2 = 0.973$) and a strongly significant p of 0.059, with q still insignificant. Similar fits were obtained with weekly data ($\bar{R}^2 = 0.963$).

The monthly tracking study collected data on Optus trial regularly. Consideration, conversion to Optus loyal, and call allocation were only measured after six months. Therefore, for detailed model flow-rate validation, a diffusion model could only be fit to trial data. Taking α_T from the prelaunch logit model, fitting six months of trial gave a fitted p_T of 0.386 (compared with the prelaunch estimate of 0.347), and an $\bar{R}^2$ in the rate model of 0.931. Consideration and Optus loyalty survey results after six months enabled estimates of these rate parameters to be determined, but not for their statistical accuracy to be examined. Consideration after six months was 0.54, giving $p_C = 0.242$, very close to the prelaunch estimate of 0.231. The rate of flow from trial to Optus loyalty, p_L, was estimated to be 0.155, again similar to the prelaunch forecast of 0.198.

While we have tested our model calibrated prelaunch against actual sales data and behavior, it is difficult to work out the benchmark models against which it should be compared. Because it subsumes a static choice model, it is easy to observe the cost of omitting dynamics (see Table 5A). Given the measures that we collected, it is not easy to compare it to other dynamic brand-choice models.

Further Applications and Transportability

The model has been applied to other types of telecommunications markets in a number of countries (B2B with business toll calls, subscription services with cell phone adoption, and global with international calls), as well as other industries, including domestic air travel. In the Australian domestic air travel market we were faced with two defenders and two new entrants. One advantage of the semi-Markov approach is its flexibility. We could use a nested logit model (with one level being choice of established or new carrier and the other choice of airline), calibrating the inclusive value of new and established carriers. The other approach was to have multinomial flows from the dynamic equilibrium of the two established airlines to the four airlines after launch. After examining the market structure, we chose the former formulation.

The question naturally arises as to where our model would be most useful. Given its prelaunch nature, ability to handle dynamics, and strong choice basis, the approach seems appropriate in any market in which market turbulence due to new entry (or even changing competitive advantage) is imminent. Obvious examples of this include defense against entry due to deregulation (e.g., electricity markets), entry due to technology change (e.g., Intel versus AMD and Microsoft versus Linux), entry due to changing standards (e.g., Beta versus VHS recording formats), and entry due to products coming off patent (e.g., Pfizer's Lipitor in the pharmaceutical industry and Du Pont's Lycra in the clothing industry).

Conclusion

In contrast to most applications of research on emerging innovations, we have examined the managerial problem facing the incumbent rather than the new entrant. We developed a dynamic closed-form six-state model of choice incorporating defensive marketing actions as well as the new entrant's marketing mix. We applied the model to defense against new entry in an existing category, estimating prelaunch dynamics based on respondent data. Six months after launch, we validated the model. Challenges facing the defender that were highlighted in the application can be illustrated by the diagram below:

	Enhance and communicate own strengths	Exploit and expose entrant's weaknesses
Reduce equilibrium appeal (Equations (1), (2), (4)–(7))	Positive strategies	Negative strategies
Slow rate of diffusion (Equations (3), (8)–(10))	Inertial strategies	Retarding strategies

Positive strategies to enhance the defender's strengths and thus improve equilibrium share include stressing new features and prices, as well as communications that exploit its strengths (e.g., "Telstra has improved a lot"). *Negative strategies* that attack weaknesses of the new entrant include emphasizing the new entrant's risk, because information uncertainty is greatest at launch. By talking of trust, other heritage attributes, and uncertainty, this weakness of the new entrant may be emphasized. Strategies targeted at the rate of diffusion may include *inertial strategies*, which strengthen the incumbent's hold over its customers (e.g., contracts, lock-in strategies, and psychological appeals). Alternatively, they may involve *retarding strategies* to make it harder to choose the new entrant. For example, in the U.S. market, AT&T suggested, when MCI launched its Friends and Family Program promising a large saving, that potential customers should "get it in writing." This had the effect of making changing a toll-call provider a hassle, thus retarding conversion. Much of the diffusion of innovations literature (e.g., Rogers 1995) suggests inertial ways to slow diffusion rate (e.g., the role of compatibility and complexity).

By looking at drivers of flow rates and flow levels, our model provides ways of addressing each of these four defensive challenges. Calibrating the model helps the defender avoid fighting on unwinnable territory (e.g., it would be pointless to claim that Optus will not deliver to this market, given strong and universally accepted attitudes to the contrary). While static choice models used for defense may assist with understanding the ultimate appeal of the new entrant and how that can be limited, they miss an important aspect by ignoring the dynamics of share gain. When we move from the base model to the detailed model, we identify specific defensive leverage points in the consumer decision process, and thus give the manager finer information as to how to conduct the defense process. The managerial use of the results of this model led Telstra's Corporate Marketing Director, Charlie Zoi, to say, "This is the single most influential piece of market research that this organization has ever undertaken."

This approach has a number of limitations. For the sake of parsimony, we have assumed that flow rates from one state to different destination states occur at the same rate. Future research could relax this assumption. We have assumed that there are no supply constraints, reasonable in this case, but not always. We segmented on the basis of usage as a proxy for taste heterogeneity, whereas estimating a model with unobserved heterogeneity would have been preferable. Also, a one-step estimation of the detailed model would have had better statistical properties than the estimation by decision stage that we undertook.

Finally, while advertising data were available during the first six months, given the short period and the collinearity between advertising and Optus share growth, it was impossible to calibrate their effect. Clearly, advertising is an important management decision variable, and its effects should be incorporated into the changing attitudes of both companies.

The objective of this paper is to demonstrate that dynamic defense models are accessible to managers and to show how they may be calibrated prelaunch in practice. These models provide detailed diagnostic information to evaluate defensive strategies. When combined with normative models in competitive strategy, they provide the pay-off matrix from which game-theoretic solutions may be derived. The contributions of the paper are a closed-form model of dynamic defense, a measurement methodology that includes prelaunch calibration of diffusion and choice parameters, forecast validation, and a major industry application that helps in the link between marketing modeling and marketing management in practice. The paper provides a first step in understanding the dynamics of defense in specific markets and also in incorporating the defenders' marketing mix into dynamic choice models.

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