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The Inaugural ISMS Practice Prize Competition

ISMS Practice Prize Competition Chairman
Gary L. Lilien: "Special Section Introduction by the ISMS Practice Prize Competition Chairman"

Finalists
Joseph A. Foster, Peter N. Golder, Gerard J. Tellis: "Predicting Sales Takeoff for Whirlpool's New Personal Valet"

John H. Roberts, Pamela D. Morrison, Charles J. Nelson: "Implementing a Prelaunch Diffusion Model: Measurement and Management Challenges of the Telstra Switching Study"

Special Section Introduction by the ISMS Practice Prize Competition Chairman

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In 2003 the INFORMS Society for Marketing Science (ISMS) introduced and conducted its inaugural Practice Prize Competition. The reports and papers that follow are the finalists from that competition, representing the best examples of rigor plus relevance that our profession produces.

Key words: marketing science practice; database marketing; diffusion; prelaunch forecasting; market entry; defensive strategy; segmentation
History: Processed by Gary L. Lilien, ISMS Practice Prize Editor.

Background

ISMS's bylaws state that its purpose "… is to foster the development, dissemination, *and implementation* of knowledge, basic and applied research, and science and technologies that improve the understanding and *practice* of marketing."

Note the emphasis on implementation and on practice. The Society's goals are well served by its journal, *Marketing Science*, and it has recognized outstanding new developments each year since 1982 through the John D. C. Little Best Paper Award and each year since 1990 through the Frank Bass Award for the best paper related to a doctoral dissertation.

Those two awards focus primarily on the scientific merit of the work. However, they do not explicitly recognize the practice and implementation aspects cited in the Society's charter. To address this need, the Society established the ISMS Practice Prize. According to the Prize protocol, the Practice Prize is awarded for an outstanding implementation of marketing science concepts and methods. The methodology used must be sound and appropriate to the problem and organization, and the work should have had significant, verifiable, and preferably, quantitative impact on the performance of the client organization. Any work completed in recent years is eligible; prior publication of the work does not disqualify it.

In other words, the award is designed to recognize both the rigor of the work and its focus on relevance and organizational impact. Specifically, the following criteria have driven the selection of finalists and the winner:

Implementation—Who uses it, for what, and how
Impact—Organization and what value
Methodological Quality—Leading edge/appropriateness
Technical Originality—Uniqueness and flair
Difficulty—Problem(s), politics, and technical
Transportability—Use in other applications or similar organizations
Charm—Impact on society or newsworthiness

The Competition

The Inaugural 2003 Competition was a rigorous one. The prize committee, comprised of Ed Brody, Abbie Griffin, Gary Lilien (Chair), Arvind Rangaswamy, Jorge Silva-Risso, Joel Steckel, and Steve Shugan, received 31 excellent entries, each of which described both the work itself and the impact that the work has had on the client organization.

From that set of 31 entries, the judges selected the three finalists whose work is reproduced here. Those finalists presented their work to the prize committee at the 25th Marketing Science Conference at the University of Maryland in June 2003. It is gratifying to note that these finalists represent three different continents, demonstrating the global reach of Marketing Science.

The Three Finalists

The contribution of Joseph A. Foster, Peter N. Golder, and Gerard J. Tellis is entitled "Predicting Sales Takeoff for Whirlpool's New Personal Valet." In that work they describe the situation facing the Whirlpool Corporation, a major U.S. manufacturer of consumer durables, test marketed the Personal Valet Clothes Vitalizing System in 2001 and launched it in 2002. The Personal Valet is the first in a new category of appliances: A substitute for dry-cleaning services, providing an in-home service to customers, replacing a service currently performed outside the home. Hence, it generates significant cost savings and added convenience for consumers. Management needed a sound model for the timing of sales takeoff. The project manager applied Golder and Tellis's (1997) the "time-to-takeoff model" of which correctly identifies takeoff over 90% of the time. Instead of projecting a linear pattern of sales in the first few years, the project manager used the model to project 10-year sales with takeoff in the 6th year. He also simulated various pricing and product modification schemes to predict time and probability of takeoff. In the absence of the model, the accounting department, using linear growth, would have forecast much higher sales than is typical for such a new consumer durable as shown by our model. Such forecast would have led to disappointment with actual sales (which were low) and to premature termination of the project. A report on that project follows; more complete technical details are available in Golder and Tellis (1997, 2004).

The contribution of John H. Roberts, Pamela D. Morrison, and Charles J. Nelson is entitled "Implementing a Prelaunch Diffusion Model: Measurement and Management Challenges of the Telstra Switching Study." They describe the situation that Telstra, the Australian telephone company, was facing with the threat of competitive entry by a major rival, Optus and, hence, sought help in developing a defensive marketing strategy. The problem was to assess the obtainable market share of the new entrant in the residential Australian long-distance telephone call market, to gauge how quickly that share would be gained, and determine the factors that would influence its dynamics and ultimate market appeal. They developed probability flow models to provide a framework to generate forecasts and assess the determinants of share loss. Telstra used the models to set prices adaptively, direct service initiatives, design advertising copy, and dimension the network (including financial and manpower planning). Decisions based on the model included a move to compete on service (rather than price), including specific service components; a decision not to oppose an early move to preselection by Optus; the setting of actual price levels and formats; a targeting plan for telemarketing; and dimensioning decisions based on model forecasts. Telstra avoided head-to-head price plan comparisons, representing an increase in contribution of $US22 mm per year and other benefits of the model application led to incremental revenue of over $US50 mm a year. Again, we have a report of the work here with more details available in Roberts et al. (2004).

The winning entry, by Ralf Elsner, Manfred Krafft, and Arnd Huchzermeier, is "Optimizing Rhenania's Direct Marketing Business Through Dynamic Multi-Level Modeling (DMLM) in a Multicatalog-Brand Environment." Rhenania, a German direct mail-order company, used the model to answer the most important direct marketing questions: When, how often, and to which people in the customer base should the company mail? The uniqueness of their approach is (1) it dynamically evaluates customers based on their past purchase history and (2) it derives a threshold level of sales per customer needed to maximize profits in mailing campaigns over time and across multiple-customer segments. That approach was so effective that in a relatively short period of time after introducing the model, Rhenania acquired two of its major competitors, including a subdivision of the Springer Publishing Company, which dwarfed it in size. The full paper describing the application is available here.

Acknowledgments
I would like to thank the members of Practice Prize Committee for all of their work in helping to make this inaugural competition such a successful one, and the Marketing Science Institute for helping to sponsor the competition. On behalf of the Prize Committee, I would like to congratulate the finalists and winners for their outstanding work and contributions to the practice of marketing science!

A Final Note

Excellent DVDs of these presentations in chapter format are available for adoption for illustration or classroom use. The DVDs also have the PowerPoint presentations that the presenters used at the competition. To purchase the videos, see the advertisement elsewhere in this issue or go to http://www.informs.org/Edu/MarketingScience/.

Predicting Sales Takeoff for Whirlpool's New Personal Valet

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The introduction of really new products creates many dilemmas for managers. Initially, they must develop a launch strategy in the face of great uncertainty about the product's potential. After launch, they need guidance about whether to pull the plug on a new product with lackluster sales (prior to takeoff) or persist with a product that could ultimately be a failure. Our results and model of the takeoff in sales of new products provide some guidance on these complex managerial decisions.

Prior to our study on sales takeoff, a manager's only recourse to analyzing new product growth would have been diffusion models. However, these models have typically used new product sales beginning at or around the takeoff, have assumed takeoff, and have not explicitly modeled it. In contrast, our model addresses the time from commercialization until takeoff, thus providing insights during the period of greatest uncertainty.

Whirlpool Corporation used our model to guide their decision making in the testing and launch of a completely new consumer durable, the Personal Valet.

Key words: sales takeoff; new product growth; product management; sales forecasting; market response models; innovation
History: Processed by Gary L. Lilien, ISMS Practice Prize Editor.

Company and Problem Background

Whirlpool Corporation is the world's leading manufacturer and marketer of major home appliances. Every year, it sells $11 billion of appliances under 11 brand names in more than 170 countries. In the 1990s, Whirlpool developed the first new appliance category in 30 years. The product is a laundry appliance called the Personal Valet Clothes Vitalizing System (www.personalvalet.com). It is the first in a new category of appliances: a substitute for dry-cleaning service. It can be placed in bedrooms, walk-in closets, or laundry rooms because it runs on standard 110-volt electricity and does not require any water lines or other special hookups. Through a patented process, the Personal Valet smoothes wrinkles and cleans odors from virtually every fabric, such as wool, silk, cotton, leather, suede, and synthetic clothes, thus eliminating two primary reasons for trips to the dry cleaner. It cannot remove visible stains, but only about one-quarter of the clothes taken to dry cleaners need to have visible stains cleaned. Treating up to three items of clothing at a time in the Personal Valet takes 30 minutes or more, depending on the cycle selected. The product costs about $1000, including installation.

The Personal Valet satisfies the majority of consumers' needs for dry-cleaning services, without the time and expense of going to the dry cleaner. Currently, U.S. consumers spend over $8 billion annually on dry cleaning services, and ironing is the second most disliked household chore, just behind washing windows. Thus, the Personal Valet has the potential to significantly increase consumer welfare through cost savings, increased convenience, and reduced drudgery.

When we began working with Whirlpool in 1996, our initial work on sales takeoff (Golder and Tellis 1997) had not yet been published, so there were many unanswered questions about the market response to really new consumer durables:

What is the typical pattern of early sales for new durables?
Is there a takeoff?
What is the time to takeoff?
Does takeoff have systematic patterns?
Can we model and predict takeoff?
Can we manage the timing of takeoff?
How do we price the product?
How much should we spend on advertising?
How should we distribute the product?

Approach to Solution

We began our analysis in this project by expanding the data set beyond the 31 categories included in Golder and Tellis (1997). We sought to include additional kitchen and laundry appliances and more recent categories. The broadened data set includes carbon monoxide monitors, bread makers, espresso machines, PDAs, and scanners. Based on our expanded data set, we developed insights and recommendations in three key areas.

Patterns of Early Sales and Takeoff for Really New Consumer Durables

Our answers to Questions 1–4 above are summarized in a number of descriptive statistics and sales curves (Golder and Tellis 1997, 2004). Overall, these findings indicate that it takes several years to reach a distinct takeoff in sales. On average, the time-to-takeoff is 10 years, and sales at takeoff increase more than 400%. Golder and Tellis (1997, 2004) report many additional findings on unit sales, price declines, price points at takeoff, and penetration. For kitchen and laundry appliances, average time from commercialization to takeoff is 15.6 years, but only 5.8 years for the subset of these categories introduced after World War II.

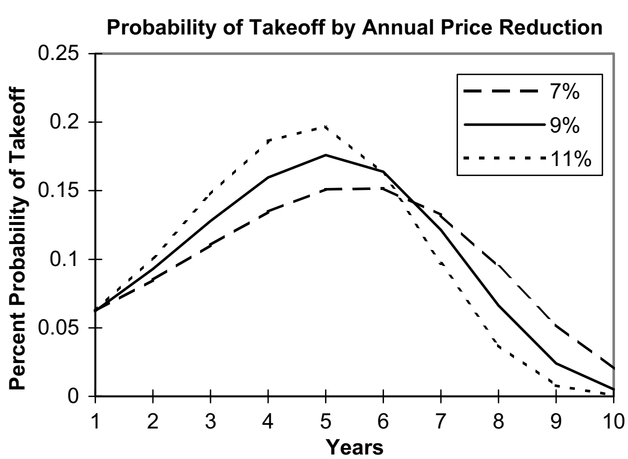
Modeling and Managing Takeoff

Prior to our work on sales takeoff, managers may not have been aware that a dramatic takeoff was a common occurrence with new durables. Since this takeoff is the critical event in the life of a new product, our model of takeoff was of particular interest to Whirlpool in answering Questions 5–7 above.

The most important result from our model was the determination of the marginal probability of takeoff over time. As inputs to the model, we used managerial judgments about planned price declines over time. Also, we evaluated a variety of scenarios about market penetration over time based on historical patterns of penetration for relevant subsets of categories. Figure 1 is representative of the results generated in this analysis. The percentages are three different annual price reductions. Penetration for all three curves is the average penetration in each year for a representative set of kitchen and laundry appliances.

Using such analyses, Whirlpool could evaluate how different pricing strategies would impact the probability of takeoff for the Personal Valet. Note that larger price reductions increase the peak probability of takeoff and shorten the time at which the peak occurs.

Figure 1 Annual Price Reduction



We predicted the year of takeoff to occur when the cumulative probability exceeded 50%. In addition, our research indicated that price points of $1,000 and $500 could be relevant for the Personal Valet's takeoff. Overall, based on our analysis of similar categories and Whirlpool's planned strategy, we expected that the time-to-takeoff would be about 10 years.

Impact on Other Elements of Marketing (Distribution and Advertising)

While our model did not include marketing variables other than price, the prediction of a long time-to-takeoff had important implications for other marketing variables (Questions 8 and 9 above). In particular, low levels of advertising and focused distribution would keep costs under control during the initial period of low sales.

Implementation Challenges

The prediction of a long time-to-takeoff and the strategy resulting from this prediction led to two general concerns. First, how could we be sure that we were using the right set of products as the standard for the Personal Valet? After all, alternate products could lead to different parameter estimates and different penetration paths over time than the ones we were using. We addressed this concern through a variety of sensitivity analyses and found that several plausible alternate products led to the same conclusions. For managers considering other types of products, we provide some guidance by showing various median times to takeoff in Table 1.

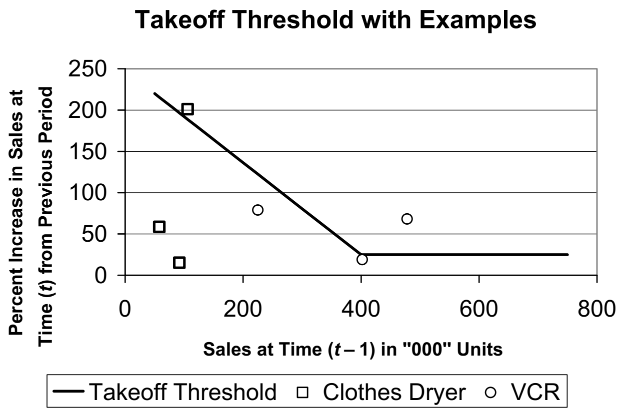
A second concern was whether it was possible to validate the takeoff as it occurred or whether it would only be known one or two years later. To address this concern, our threshold rule for takeoff can be useful (Golder and Tellis 1997). This rule can classify whether a new product's sales growth relative to the previous year's growth in sales is high enough to

Table 1 Various Median Times to Takeoff

Categories	Sample size	Median years until takeoff*
All	40	8.5
Pre-World War II	16	15.0
Post-World War II	24	5.5
1965 and later	21	5.0
1980 and later	11	4.0
Kitchen and laundry	14	12.0
Time saving	24	8.5
Leisure enhancing	19	8.0
Electronic	21	6.0
Nonelectronic	19	15.0
High price at commercialization (>$950)	19	9.0
Low price at commercialization (<$950)	21	5.0

* Year 1 is the year of commercialization.

Figure 2 Sales Increases for Clothes Dryers and VCRs at Takeoff and in the Two Years Prior to Takeoff



signal a takeoff. A takeoff means that the category has transitioned into the growth stage of the product life cycle. Here, sales can be expected to increase substantially for about eight years, on average (Golder and Tellis 2004). In contrast, a false takeoff would be a reasonably large sales increase, except that the product would continue in the introduction stage of the product life cycle.

Here are the steps that managers should take to apply the threshold rule in evaluating their new product. First, they should remember that the threshold rule is relevant only after a category is being sold; it cannot be used to predict takeoff prior to commercialization. Second, companies can then plot the percentage increase in sales versus base sales in the prior year. Third, the first data point above the threshold signals the takeoff. This rule was accurate in more than 90% of the categories in Golder and Tellis (1997). Data points well above the threshold indicate higher probability of takeoff. In Figure 2, we plot sales increases for clothes dryers and VCRs at takeoff and in the two years prior to takeoff. The threshold rule helps to differentiate between large sales increases that do not signal a takeoff from those that do.

Impact of Results on Whirlpool's Decision Making

Our work for Whirlpool had several effects. Without our model, Whirlpool would have likely forecasted linear sales growth. These forecasts would have predicted much higher sales than the product is currently generating. This discrepancy between unrealistic expectations and actual sales may have put pressure on managers to pull the plug on the Personal Valet.

With our model, Whirlpool has a greater understanding that really new products require a number of years to takeoff. The analysis with our model predicted that the Personal Valet would take about 10 years to takeoff in the mass market. (Note that laundry dryers took 20 years to reach about 10% household penetration, and microwave ovens took about 15 years to reach that penetration level. Even though most of us cannot imagine living without these appliances today, their penetration of the market did not happen quickly.)

This understanding led Whirlpool to be more cautious in its launch strategy. In August 2002, they launched the product into only the Contract Channel (i.e., contractors who build or remodel homes) and not into the mass market. According to Dave Herbert, Whirlpool's director of new business development, "Whether you are building a new home or are interested in having a Personal Valet system installed in your current home, your local ACD (authorized contract distributor) is an ideal place to learn more about it." This focused distribution strategy provided an excellent route to sell the Personal Valet while the market as a whole had almost no awareness or knowledge of the product. Such a cautious approach would limit losses and give the product time to succeed.

In contrast, TiVo spent more than $200 million on sales and marketing for their new product. Yet, after 4 years, the product did not takeoff and achieved less than 1% cumulative penetration. Similarly, the peak annual pretakeoff advertising was at least several million dollars for fax machines, pagers, carbon monoxide monitors, microwave ovens, CD players, cell phones, and camcorders. Such expenditures contributed to early losses. Instead, building awareness and word of mouth in focused markets can help when the firm is ready for its mass-market launch.

Transportability of Model and Results

Our model and results on the sales takeoff can be usefully applied to many other new products including the much-publicized Segway scooter, DVD recorders, HDTV, and personal video recorders like TiVo. Managers of such products can benefit from the median times to takeoff, the application of the threshold rule, or the application of our model for predicting takeoff. In this section, we address two additional key questions.

What if my new product never takes off?

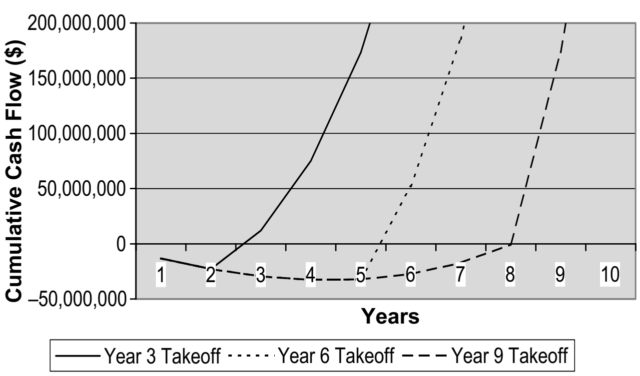
All of the new products in our current data set eventually had a takeoff in sales. However, our model can still be used to help managers decide to pull the plug on a new product. Consider a situation where the model indicates a high probability of takeoff, yet the product has not taken off. Here, managers could conclude that their new product is unlikely to take-off as have the successful products in our sample. In addition, our threshold rule can be used to determine how far away the product is from achieving the conditions necessary for takeoff.

How long will it take to achieve positive cash flow?

Several variables impact the duration to achieve positive cash flow or become profitable. We developed a simple spreadsheet model of this process, which is available from the authors upon request. Data for the variables in the model come from several sources. First, unit sales and growth rates over the product life cycle come from Golder and Tellis (2004). Second, cost declines over time can be estimated from experience curve effects (Abell and Hammond 1979, Day and Montgomery 1983). The first two inputs are for the U.S. market. Managers can easily use the model for other countries by using input from those countries (e.g., Tellis et al. 2003). Third, each company must provide prices, initial costs, and marketing expenditures. Finally, we consider three different predictions about the time to takeoff (3, 6, and 9 years), based on results in Table 1.

The following specific data are used to calculate the cumulative cash flow curves in Figure 3:

Figure 3 **Takeoff as Critical Event in Future Cash Flow of a New Product**



Based on Company Input

Price at commercialization: $500.

Annual % price decline: 7%.

Manufacturer's cost/price at commercialization: 90%.

Annual marketing expenditures: $15 million.

Based on Previous Research

Experience curve %: 80% (see Abell and Hammond 1979 for summary).

Sales at commercialization: 34,000 units (Golder and Tellis 2004).

Annual growth rate during introduction stage: 31% (Golder and Tellis 2004).

Growth rate at takeoff: 428% (Golder and Tellis 2004).

Annual growth rate during growth stage: 45% (Golder and Tellis 2004).

As easily seen in Figure 3, the takeoff is the critical event in the future cash flow of a new product. Even after years of cash outflow, cumulative cash flow turns positive at takeoff. After takeoff, cash flow increases dramatically. These results indicate that firms should strongly consider lower prices and higher marketing expenditures, even with larger losses, in order to achieve a faster takeoff. Authors have long emphasized the importance of such a financial analysis (e.g., Kotler 2003).

Conclusion

There is tremendous uncertainty about the potential success of really new products and the right marketing strategy to achieve that success. For Whirlpool, our findings and model of the sales takeoff helped to resolve at least some of this uncertainty with their new Personal Valet. Much research remains to be done on new products, but our model does provide a scientific basis for generating insights on the sales takeoff by incorporating historical data and managerial input.

Implementing a Prelaunch Diffusion Model: Measurement and Management Challenges of the Telstra Switching Study

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This paper describes the challenge of applying a marketing science model in practice and the benefits from doing so. There have been many tools developed in marketing science, but their use and impact have often been disappointing (e.g., see Steenkamp 2000). One major reason for this is the difficulty of adapting our models to the managerial context at which they are targeted (including ensuring completeness, providing timeliness, and calibrating total effects). Another is achieving organizational adoption of the model findings and translating analytical insights into marketing actions. In this paper the context in which actions need to be focused is the preparation of a defensive strategy prior to the launch of a new entrant. While the two major problems of managers are growth and defense, use of marketing science models for the latter is less prevalent than for growth (with, for example, choice-based conjoint analysis and diffusion modeling. (See Dick R. Wittink and Trond Bergestuen. 2001. Forecasting with conjoint analysis. J. S. Armstrong, ed. *Principles of Forecasting: A Handbook for Researchers and Practitioners*. Kluwer Academic Publishers, Boston, MA and V. Mahajan, E. Muller, and Y. Wind, eds. 2000. *New Product Diffusion Models*. Kluwer Academic Press, Amsterdam, The Netherlands.)

Key words: choice models; competitive strategy; defensive strategy; diffusion; market entry; market response models; prelaunch forecasting
History: Processed by Gary L. Lilien, ISMS Practice Prize Editor.

We consider the problem of implementing a marketing science model for the Australian telephone company, Telstra, prior to the deregulation of the long-distance toll-call market as it faced competition from a new entrant, Optus Communications. We review the type of information it needed to focus marketing actions prior to Optus's launch and the market research and modeling necessary to obtain that information. After calibrating a model of market response to Optus's possible market positioning and pricing strategies and Telstra's potential reactions to them, we identify the insights that this model provides in directing defensive strategy. We then discuss challenges of implementing the results across the organization and the benefits of doing so.

Management Problem

For a model to be useful it must be focused on the management actions that it wishes to influence. Therefore, we begin by looking at the information that Telstra needed and the actions that would be supported by that information. Deregulation of the Australian long-distance toll-call market and impending entry of Optus, a subsidiary of Cable and Wireless of the United Kingdom and Bell South from the United States, provided Telstra with two types of challenges: how to minimize and slow market share loss (requiring diagnostic information) and how to estimate the extent of the loss for planning purposes (prognostic information). The management actions that would be used to control Optus's growth were pricing (including price levels, pricing formats, and route-by-route prices), customer communications (including advertising copy and spend, as well as customer service levels), and account management strategies (including selective protection of desirable customers and up-selling and cross-selling). In terms of planning, forecasts under likely scenarios were required by Engineering groups for network provisioning, by Manpower Planning for recruitment and training, and by Finance for capital raising and budgeting. These strategies and plans had to be in place prior to the launch of the new company's service.

To meet these needs, marketing models had to estimate response functions for both Optus's initiatives and Telstra's response to them in terms of price and perceived service levels. Both equilibrium loss of share and the rate at which that loss would occur were required under different scenarios to enable Telstra to test and optimize its reaction to the new entrant.

Solution Approach

The management information required calls for a model that is flexible with respect to phenomena, can explain consumer adoption in terms of environmental and management decision variables, and can forecast the rate at which market evolution will occur. Semi-Markov models present a rigorous method to address these prerequisites (see Hauser and Wisniewski 1982).

Calibration of a semi-Markov model consists of three stages: specification of behavioral states, determination of relative flow levels between states, and calibration of flow rates. One subsidiary advantage of this flexible framework is that flow levels can be estimated using discrete choice models while flow rates may be estimated using diffusion or hazard rate models, thus algebraically subsuming two of the major modeling traditions in marketing. We implemented the model at two levels of complexity in keeping with the use of evolutionary model building by Urban and Karash. In this paper we describe only the base model. This base model, illustrated in Figure 1, shows how the ultimate flow levels and the rates at which those levels will be achieved can be modeled in terms of their determinants.

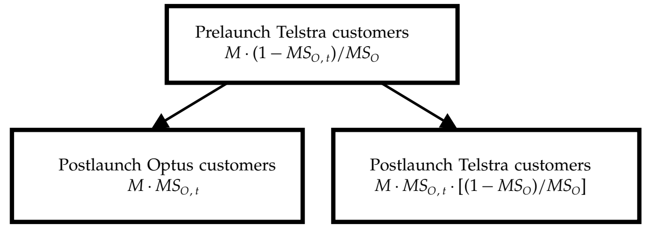
The Measurement Challenge

To implement the model illustrated in Figure 1 we need to be able to represent the new entrant to the target market and gauge its reaction. Therefore, we need a stimulus, a sampling frame, and a set of measures with which to calibrate the model.

Stimulus

Future adoption forecasts based on prelaunch market research may be obtained from behavioral intentions, which depend on consumers' perceptions. Because consumers are likely to have less than full information about a service prior to its launch, it is necessary to construct a stimulus to represent it along the salient choice dimensions. In conjoint analysis this is performed using a concept description or storyboard. For products or services with which the consumer is unfamiliar this may be achieved by information acceleration (Urban et al. 1997). In our application, qualitative research showed that the key choice dimensions on which consumers would judge Optus were its pricing and positioning strategy relative to Telstra and their inertia and attitude to switching. A key part of the research was collecting competitive intelligence to ensure that the stimulus truly represented the service offering that Optus would provide. We forecast Optus's positioning strategy from their job advertisements, publicity, and executive profiles. Optus's probable pricing came from discussion with trade sources.

Figure 1 Model of Optus Penetration: Its Dynamics and Determinants



(a) Flow levels:
Logit model of equilibrium choice:

$$MS_O = \frac{m}{M} = \frac{e^{U_O - I}}{e^{U_O - I} + e^{U_T}}$$

where

$$U_j = \sum_{k=1}^{K} w_k x_{jk} - \lambda c_j$$

(b) Flow rates
Bass model of diffusion flow:

$$MS_{O,t} = \frac{m}{M} \cdot \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}$$

Combining the ultimate flow level with the flow rate above gives the market share of Optus at time t:

$$MS_{O,t} = \frac{e^{U_O - I}}{e^{U_O - I} + e^{U_T}} \cdot \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}$$

where M is the population size, $MS_{O,t}$ is the share of Optus at time t, MS_O is Optus' ultimate share, U is utility, I is inertia, x_{jk} is the level of attribute k for company j (*for* $O =$ *Optus and* $T =$ *Telstra*), w_k is the importance weight of attribute k, λ is the opportunity cost of money, c_j is the price of company j's service, and p and q are Bass' rate parameters.

Sampling Frame

Telstra had names and addresses of all toll call users, and we surveyed 800 toll-call users via systematic sampling, followed by face-to-face interviews.

Measures

We measured perceptions using standard Likert scales and behavioral intentions using an 11-point Juster scale. Attitude items were of two types: attitudes towards Telstra relative to Optus and attitudes to switching and inertia. For diffusion rate parameters we departed from the standard use of managerial judgment and used consumer feedback. We asked respondents how long it would take to make a decision. For convergent validity we also calibrated rate parameters using analogy to a previously deregulated overseas market. One advantage of using consumer feedback to calibrate the rate parameter is that we can relate the time it takes consumers to make a decision to their attitudes to Telstra relative to Optus, switching and inertia, and background variables.

Figure 2 Results of Model Calibration

Diagnostic Results: Using Model Results to Focus Actions Controlling Market Share Loss

(a) Reducing ultimate share loss
Logit model on intentions

Parameter	β	s.e.
Price difference	0.75	0.04
Price difference^2	−0.23	0.05
Optus price discount	0.20	0.05
Telstra price discount	−0.16	0.04
Relationship with Telstra	−0.11	0.09
Downside	−0.32	0.09
Restlessness	0.39	0.09
High inertia	−0.24	0.08

Fit $L(0) = -2{,}216$ $L(B) = -1{,}789$ $\chi_9^2 = 85$

(b) Reducing rate of share loss
Regression on decision time

Parameter	β	s.e.
Telstra not responsive	−0.12	0.04
Teach Telstra a lesson	−0.08	0.04
Saving only reason	0.10	0.04
Optus might be risky	0.20	0.05

Fit R^2 adjusted = 0.10

Prognostic Results: Using Model Results to Forecast Market Share Loss

(c) Forecasts of ultimate share loss
Logit model on intentions
Core price planning scenario 1
(Perceived price parity):

$$M_O/M = 0.22$$

Core price planning scenario 2
(Optus perceived price advantage of 5%):

$$M_O/M = 0.33$$

(d) Forecasts of rate of share loss
Bass model (stated decision time and analogous market share)

	Self stated		Analogy	
	β	s.e.	β	s.e.
m	1.00	—	0.45	0.03
p	0.05	0.01	0.06	0.00
q	0.05	0.06	−0.01	0.02
R^2	0.972		0.973	

Model Results and Their Implications

Perceptual measures and the dynamic behavioral intentions based on them were used to calibrate the model illustrated in Figure 1. The results, summarized in Figure 2, show the determinants of ultimate share and the determinants of share loss rate in the top two boxes (see Figure 2a, b). Market share will be lost depending on price (but in a decreasing way given the significance of the squared term). Price discount plans (under which consumers sign up for cheaper packages) are more effective for Optus than for Telstra in determining share loss. Risk aversion (perceived "downside" of switching) and barriers to switching ("high inertia") lead to lower ultimate loss, while the drivers of switching ("restlessness") lead to higher ultimate loss. In terms of the flow rate of the loss, a perceived "lack of responsiveness" by Telstra and a desire to "teach Telstra a lesson" lead to fast decision making, while "risk aversion" slows it down. Those only switching to "save money" are in no hurry to make a decision.

These drivers of switching assisted Telstra to fine tune its response after assessing Optus's most likely moves. Given the expected positioning and pricing strategy of Optus and Telstra's planned response to it, we needed to generate forecasts of share loss. The ultimate share loss came directly from the logit model described in Figure 1a and estimated in Figure 2a. At perceived price parity, Telstra could expect to lose 22% of the market. The rate at which that share loss would occur can be obtained by estimating the Bass model on either self-stated decision times or data from the U.S. market (see Roberts et al. 2005 for details). Both sets of data yielded an insignificant coefficient of internal influence (q) and a coefficient of external influence (p) of 0.05–0.06. (When the equation is re-estimated without q, there is no statistically significant difference between the two estimates of p.)

Managerial Implications of Results

Telstra's Preresearch Proposed Strategy

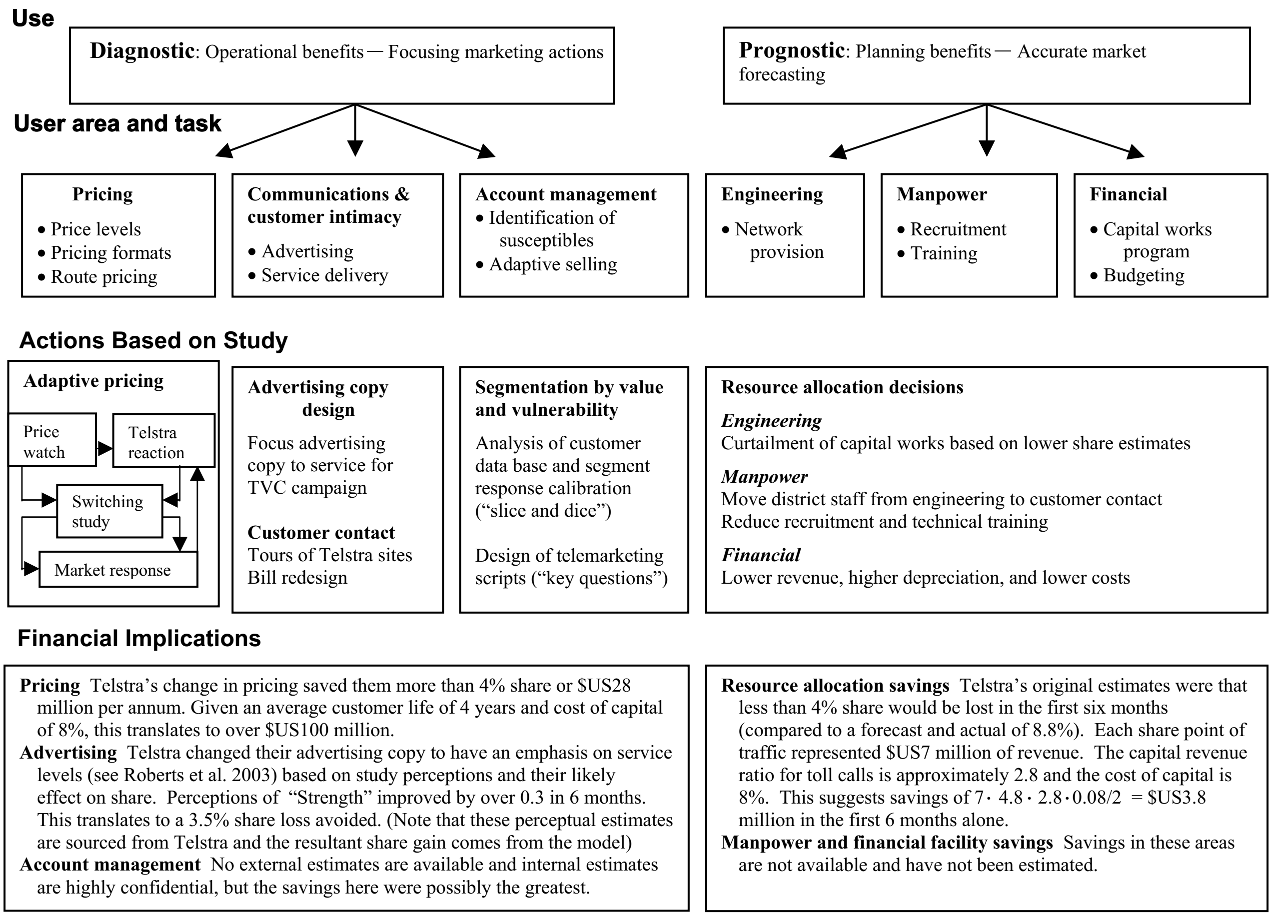
Telstra's original planned strategy prior to the research was to use price as a blunt instrument to protect market share using across-the-board cuts. Advertising copy was to be targeted at boasting of the technical prowess and reach of the organization. Planning groups were expecting Telstra to lose 4% of the market in the first 6 months, based on this proposed strategy.

Diagnostic Insights

Insights from the Telstra Switching Study came from both an examination of the raw data and the more complex application of the base and detailed models (see Figure 3 for a summary).

Pricing. The asymmetry of Telstra and Optus price plan effects in Figure 2a meant that Telstra would suffer if it fell into a price war (a problem exacerbated by the fact that it had a higher cost structure and would lose margin on a bigger base). Two factors suggested an alternative. First, a segmentation study (not reported here) indicated that price plans with an entry price would protect the valuable vulnerable

Figure 3 Telstra Switching Study Impact Summary



customers but would not be appealing to the valuable not-vulnerable customers. Second, as the study was updated post-launch, a new category of price perception of “Don’t know” emerged. This segment was extremely prone to use Telstra. Telstra could guarantee noncomparability of prices by ensuring that it was always cheapest on some routes and at some times of day. Telstra was also able to adaptively control price, allowing fine tuning over time. It maintained a price watch, and separate modeling showed how actual prices would be translated into perceived price differences. The Switching Study then provided the market share implications of Optus and Telstra actual price changes, mediated by perceptions.

Advertising and Customer Contact. Service levels (“Telstra not responsive”) were found to be very important in determining switching intentions (see Figure 2b). Based on this finding and detailed perceptual data from the Switching Study, Telstra redesigned its bills (a major source of complaint), initiated consumer-based site visits, and promoted recent service improvements.

Account Management and Targeting. The Switching Study identified questions that gave an excellent indicator of likely switching behavior. These were used for screening who the vulnerable customers were so that telemarketing (cross-classified by size of account) could be targeted at defending the valuable vulnerables.

Prognostic Insights

The model proved to be remarkably accurate, forecasting a share loss after six months of 8.8%, the same as actual loss to two significant figures. The larger share loss forecast by the Switching Study than was previously expected by Telstra had a number of resource allocation implications. Capital works programs could be significantly curtailed. The requirement for technical staff from a maintenance perspective was reduced, and supernumerary staff were diverted to customer service and marketing functions. Recruiting and technical training budgets could also be trimmed. Finally, the financial implications of the lower share retention in terms of lower revenue (largely offset by the protection of margins through finer price management) and lower costs (both capital and labor) meant a reduced requirement for capital raising.

Implementation and Model Adoption Challenges

Challenges

The challenges of specifying and calibrating the model were ameliorated by the resources that a large organization could provide. Adequate funds for qualitative and quantitative research ensured a sound foundation. A complete sampling frame reduced sampling time and error. Excellent competitive intelligence led to accurate assumptions about Optus's likely moves.

Size, however, became a problem at the implementation stage. Telstra had more than 90,000 staff, and most were affected by the entry of Optus. Moreover, the uses for the information from the Switching Study were very diverse from price setting to the writing of advertisements to the planning of the network. Most of the target study users already had some preconception as to the likely outcome of competition and so there was a danger of "not invented here" with respect to the study findings. Timing was another major issue. The study was undertaken three months before Optus's entry, and results were provided to management one month prior to entry.

Solutions

The size issue was addressed by providing information in a way that could be easily distributed, including reports and soft copies of response functions. The diverse range of users was handled by having customized presentations to different groups specifically targeted at the actions that they would be taking. The need to reach different levels in the organization was addressed by having multiple delivery vehicles. For senior management we held seminars, for functional areas we ran workshops, for marketing analysts we provided an interactive decision support aid, all supported by reports and detailed results. We ensured compatibility by working with Telstra to write interfaces between the Switching Study and other databases and decision support tools. The need for credibility was obtained by gaining the endorsement of top management, engaging Telstra staff throughout the execution of the Switching Study, and providing adequate description of the basis of the findings. We placed considerable emphasis on technology transfer so that the Switching Study ended up being very much owned by Telstra. Finally, the very tight timeline was addressed by progressive reporting, first of forecasts giving official planning scenarios, then of response functions, and finally of all of the support tools.

Organizational Benefits

Organizational benefits from implementing the Telstra Switching Study are included in Figure 3, which summarizes the financial and tangible benefits. For a description of some of the soft benefits, see Roberts et al. (2003). These were substantial. To quote Gail Thomson, Group Manager Market Analysis, "The research was used as a critical input to fostering a competitive culture amongst Telstra's management and marketing personnel. Telstra was a large and profitable monopoly before Optus's entry to the market, and there was a sense of complacency and invulnerability regarding competition."

Operational Benefits (Diagnostic)

Telstra calculated that an accurate understanding of the response functions from the Switching Study, integrated with Telstra's other databases, saved more than $US100,000,000. Savings from better-focused advertising copy and improved targeting of individual customers were also substantial.

Planning Benefits (Prognostic)

Estimates of savings from better resource allocation were only available for the capital works program, although significant Manpower and Finance savings were also made. The expected net present value of those savings was more than $US16 million.

These savings should be compared to the cost of the project, approximately $US300,000, including the cost of Telstra personnel directly associated with it.

Summary

Market defense is an important problem. There are few marketing science applications to calibrate the dynamic response functions of both the new entrant and defender prelaunch. Implementation of such models is difficult. In this paper we have described some of the challenges in adapting our tool to the management environment, translating the insights from applying them into recommended marketing actions, and the payoff from doing so.

A problem focus and an insights-actions correspondence are necessary but not sufficient conditions for success. Organizational prerequisites include being able to use a time scale that fits within the decision process of the firm, achieving compatibility and integration with existing information systems, appropriate and relevant communication with the managers whose decisions will be based on the model's insights, and multilevel penetration of the information throughout the user organization with strong endorsement from the top.

In applying these models prelaunch there are a number of technical problems to overcome. The first of these is gaining the competitive intelligence and then designing a representation of the new product or service that will allow respondents to make accurate estimates of their future behavior. The second challenge is estimating rate parameters. Techniques for estimating equilibrium shares of new products and how these change as a function of product attributes are well established. Estimating the rate of market evolution prior to a new product's launch is more difficult (e.g., see Lilien et al. 2000). We have used consumer input, a valuable addition to management judgment and use of analogous products.

The question arises as to where the approach 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 is imminent. Examples of this include defense against entry due to deregulation (e.g., electricity markets), entry due to technology change (e.g., 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., Du Pont's Lycra in the clothing industry).

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