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A MARKET ENTRY TIMING MODEL FOR NEW TECHNOLOGIES*

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A central issue in new product development and planning is the market timing/entry decision. An entry too early may risk pushing an under-developed product into the marketplace, with possible negative results; however, a product/technology may sacrifice sales if entry is delayed too long.

A market diffusion model is developed that incorporates negative word-of-mouth associated with new product failure, resulting from premature introduction. Our analysis suggests that, when introducing a new technology, significant penalties may be associated with mistiming introduction.

The analysis was applied to a problem facing the photovoltaic program of the Department of Energy. A proposal to construct a 100-home demonstration program for photovoltaics (PV) in the Southwest was being evaluated.

The analysis of this case showed that an argument can be made to delay the demonstration program for several years and that significant risks (in terms of lowered ultimate market penetration) exist when starting this PV demonstration program prematurely.
(MARKETING, NEW PRODUCTS; DIFFUSION MODELS)

1. Introduction

We rushed to the market with a new product because it was clearly a superior technical device. We wanted to grab market share quickly. But reliability was awful. Our share peaked at fourteen percent and is now down below eight percent, while we should have had thirty or thirty-five percent of the market. A six month delay in introduction to iron out the bugs would have done it. Damn it. (Computer peripherals executive, quoted in Peters and Waterman, 1982, p. 179.)

The above is a sample of what Peters and Waterman report America's best run companies say about product quality and market entry timing. Stories about the importance of having the product "right" before introduction abound. A well-known case is the heat pump, introduced prematurely three decades ago, which required emergence of a new generation of heating and cooling engineers to give it another try in the marketplace.

The timing of new product/new technology entry in the marketplace is an important, often critical, decision. An entry too early may risk pushing an underveloped product into the marketplace, with the type of negative results illustrated above; however, a product may sacrifice sales if entry is delayed too long.

This problem is also faced by government policy makers in deciding when a new, government-supported technology is ready for public view. Such a government supported public viewing of a new technology is called a demonstration program and is usually considered to be an indication of market-readiness.

In this paper we develop a diffusion model that incorporates possible negative market feedback. We then apply that model to the analysis of a proposed demonstration program for photovoltaics (solar batteries).

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2. Model Development

Diffusion models relate the adoption rate of a new product to factors including time, population characteristics and product decision variables such as advertising and price.

Most simple models of first purchase, our focus here, follow directly or indirectly from Bass' (1969) model:

$$dX/dt = (a + bX)(N - X) \qquad \text{where} \tag{1}$$

N = ultimate adopting population,
X = cumulative number of adopters at t,
a, b = parameters to be estimated.

This model is simple and captures two effects: the diffusion effect, primarily through the multiplicative nature of the $(a + bX)$ term, and the saturation effect later on, captured through $(N - X)$. While the model does not include marketing policy variables like price or advertising, it is a parsimonious and useful description of sales patterns over time for many new products.

A number of later models have built upon this framework, incorporating marketing variables. For a review see Mahajan and Peterson (1984) and Kalish and Sen (1984) and the current collection of papers in Wind and Mahajan (1985). Mahajan and Peterson (1984) and Linstone and Sahal (1976) also provide coverage of the technological forecasting literature.

Models that have looked at advertising include Gould (1970), Horsky and Simon (1983) and Kalish (1983a, b; 1984a, b). These papers have shown then that, for the most part, advertising should be highest at introduction and then decline as fewer people are unaware and current users spread information.

A number of papers have looked at incorporating pricing over time in a monopoly. They include Bass (1980), Bass and Bultez (1982), Dolan and Jeuland (1981), Jeuland and Dolan (1982), Jeuland (1981), Kalish (1983b, 1984b), Clarke, Darrough and Heineke (1982) and Robinson and Lakhani (1975). These models have looked at price as affecting market potential as well as the rate of diffusion. Many of the models have considered optimal monopolistic pricing policies.

Models of this type assume that product feedback (handled via the coefficient b in equation (1)) is positive and constant. However, product quality/performance may change over time, and early adopters may find different levels of product satisfaction than later adopters. In diffusion models calibrated on frequently purchased items, Midgeley (1976) shows that the assumption of positive, constant product feedback is far from the case in general. More recently Mahajan, Muller and Kerin (1984) develop a model with both positive and negative feedback.

The importance of incorporating negative feedback in such models is underscored by the work of Baer et al. (1977), reporting on the relative success of 24 federally funded, new technology demonstration programs. One of their key conclusions is that failures were frequently associated with pressure to "... demonstrate before the technology is well enough developed," (p. 956)—in other words, premature market entry led to negative market feedback and resulted in program failure.

The situation we consider here is one in which product quality changes over time and, hence, customer feedback may be positive or negative depending upon the time the product is adopted. In drawing upon this literature, the model we suggest:

(1) treats market potential as a function of price. Hence as price declines, market potential increases. This assumes that consumers have a distribution of reservation prices, and that declining price allows more and more consumers to enter the market. (Kalish 1984b, Mahajan and Peterson 1978.)

(2) relates the innovation coefficient of Bass' (1969) model to the level of information communicated in the market place. This will be operationalized as a function of

advertising dollars and market demonstration dollars, both forms of product communications (Horsky and Simon 1983).

(3) allows for quality-varying customer feedback. Rather than assuming a constant, positive feedback effect, this model permits feedback to vary over time as a function of changes in product quality.

Mathematically, the model becomes:

$$S(t+1) = X(t+1) - X(t) = [N(t)h(p) - X(t)][R(A(t)) + \beta Q(t)] \quad \text{where} \tag{2}$$

$X(t)$ = cumulative number of adopters by time t,
$S(t)$ = new adopters in the tth period (current sales level),
$N(t)$ = market potential when price = 0, as a function of time,
$p = p(t)$ = price as a function of time,
$h(p)$ = fraction of market potential, $N(t)$, that finds price, p, acceptable,
$A(t)$ = 'Information level' in market place (advertising and demonstration program/communication effect),
$Q(t)$ = perceived product quality or reputation at time t,
$R(\cdot)$ = relative market response at t to $A(t)$,
β = parameter relating market response to $Q(t)$.

Equation (2) states that the number of new adopters at time t is proportional to the remaining potential $[N(t)h(p) - X(t)]$ times the probability of adoption, the second term in brackets, if both terms are positive; otherwise zero sales are assumed. The zero sales condition occurs either (a) when the potential adopter population is exhausted, because price is too high and the first term, $(N(t)h(p) - X(t))$ is nonpositive or (b) when the product is sufficiently poor that feedback is negative (second term is nonpositive). This latter condition occurs if the product is extremely poor, and initial adopters have strong negative feelings, reflected by $Q(\cdot)$ in (2) being < 0. If the sum of the nonnegative direct information term, $R(\cdot)$, and $\beta Q(\cdot)$ is less than zero, we set $S(\cdot) = 0$ in (2). This prevents negative physical sales (product returns), but indicates that customers would return the product if they could.

Note that most terms in (2) change over time: $N(t)$, the potential adopter population, changes explicitly and the effective potential $(N(t)h(p))$ changes as a function of price which in turn is a function of time. The probability of adoption (the second term is (2)) changes due to changing information levels and changing perceptions about product quality.

The direct information level $A(t)$ can be measured by the number of advertising exposures, the number of exposures to working demonstration programs or the dollar-value of investment in these forms of communication.

Perceived product quality/reputation is built and transmitted through the experience of product adopters—the word-of-mouth effect. If product quality changes over time (improving, normally, as early design and production flaws are ironed out) then the experiences of different adopters must be weighted differently, depending upon when they adopted, with early adopters normally more likely to have purchased a poorer performing version. In addition, experience with recent versions is more relevant to potential purchasers, since the versions they purchase are more likely to perform similarly to those purchased in the recent past.

Thus, we model perceived performance/quality as the sum of the expected performance impact of each model-period, weighted by the number of adopters in that period and discounted appropriately:

$$Q(t) = \sum_{j=1}^{t} P(j)S(j)\left(\frac{1}{1+r}\right)^{t-j} \quad \text{where} \tag{3}$$

$P(t)$ = expected response of adopters (i.e., $S(t)$) to the performance of products adopted in period t.

$P(t)$ is the expected performance/quality of the product—the weighted average of the possible levels of system performance where the weights reflect their impact on product reputation. There may be a number of categories of product performance and a truly poor product will have a greater negative impact than the positive impact of a good product. Letting i index the performance categories, we model $P(t)$ as $P(t) = \sum z_i(t)e_i$ where e_i is the market impact of performance level i and $z_i(t)$ is the probability that equipment sold at t has that level of performance. We assume that the market impacts (e_i) are constant in time, while the performance-category-probabilities vary (typically improve) over time.

It is instructive to expand $Q(t)$, from equation (3), as follows:

$$\beta Q(t) = \beta\left[P(t)S(t) + \frac{P(t-1)S(t-1)}{(1+r)} + \frac{P(t-2)S(t-2)}{(1+r)^2} + \cdots + \frac{P(1)S(1)}{(1+r)^t}\right]. \tag{4}$$

We see from (4) that the effect of the word-of-mouth term is that it segments cumulative sales and weights them by time of adoption. Note that if $r = 0$ and $P(t)$ is constant, then model (2) reduces to the Bass (1969) model. For $\beta = 0$, the term drops out and model (2) reduces to the Fourt and Woodlock (1960) model. It is also interesting to compare this model to that of Easingwood, Mahajan and Muller (1983). The Easingwood et al. nonuniform influence factor can be written as $b(j) = \beta X^{\delta-1}$. Thus, while $b(j)$ in their model varies by level of penetration, it does so in a very structured way and is the same for the various adopter categories.

Consider this model in the framework of adopting an alternative energy system to provide electricity for a home—a photovoltaic (PV) system. It would be mounted via a system of solar collectors on the roof of a house. $N(t)$ in this model is the stock of homes at t with roofs that could physically accommodate photovoltaics. The function h is the fraction of the owners of those homes who would consider buying a PV system and who find it potentially cost-effective at price p. That cost-effective level (reservation price) will vary due to regional differences in climatic conditions and electrical costs, among other factors.

3. Model Calibration

Diffusion models such as those of Bass (1969), Mansfield (1968) and Fisher and Pry (1971) have relied upon fit to past data for validation. These papers and those of Blackman (1974), Floyd (1968), Sharif and Kabir (1976) and others report good descriptive results: they fit historical data well. Sahal (1976) notes that it is easy to see after the fact that one form or another of an S-shaped curve will describe the phenomenon well. He concludes that:

> . . . the value of such a model is limited because it sheds little light on the nature of the underlying mechanism. More important, such a model is likely to be of little help in *prediction* because of the difficulty in choosing (especially at an early stage in the process of diffusion) a specific form from a variety of S-shaped curves that would be appropriate. (p. 230)

A diffusion model such as the one developed here is needed *before* the product is introduced. At that time, no sales data are available for parameter estimation/calibration. There are several methods that can be used at this stage:

(a) *Analogue Approach*, in which the product is assumed to behave like "comparable products." Choffray and Lilien (1986) describe a decision support system based on this approach.

(b) *Subjective Approach*, in which managerial judgment is employed formally or informally.

(c) *Experimental Approach*, in which test-market type results are used as sales figures in calibration.

While a number of methods of calibration are available, including combinations of the above (Lilien, Rao and Kalish 1981), the particular application and availability of data must dictate the most appropriate means of calibration. In the application described below, three sources were used: the output of a large-scale simulation model, designed to project market penetration of the technology assuming "good" feedback, a market survey, designed to assess the relative market impact of "bad technology" and expert judgments on the rate of improvement in the quality of the technology.

4. Application and Analysis

In 1980, the photovoltaics program of the Department of Energy received a proposal from a Southwestern builder to construct a development of 100 homes that would be equipped with photovoltaic systems. The systems would be paid for and supported by DOE funds (at approximately $75,000/home at the time); the builder would market the homes, publicize the use of the PV-systems, conduct tours of the development, etc. The builder had also obtained the cooperation of the local utility to manage the electrical load and buy back excess electricity, had arranged for appropriate building code agreements and the like.

At the time (Spring 1980) only one photovoltaic equipped home had been built. It was not occupied. Within three months after installation (a) half the installed arrays had malfunctioned in some way, (b) peak power output had declined 20 percent due to array deterioration, (c) two short circuits occurred, one serious enough to have caused a fire, and (d) no acceptable power conditioning unit had been found, commercially—such a unit was still being designed. (A power conditioning unit takes the DC current generated by the photovoltaic system and transforms and blends it with the AC current from the electric grid. It also permits output to the grid, so the homeowner can "run his electric meter backwards.")

Two questions that were addressed by the model-analysis were:

1. Is this (1980) the appropriate time to begin a demonstration program/market introduction?

2. If not, what is an appropriate time for such an introduction?

In order to use equation (2) to address these questions, we must specify certain functional forms and develop parameter estimates. For this application, the following were used:

$$h(p) = e^{-dp} \qquad \text{where } d \text{ is a parameter to be estimated,}$$

$$R_1(\,) = \begin{cases} 0 & \text{before the beginning of the demonstration program,} \\ \alpha & \text{after } (\alpha \text{ is a parameter to be estimated}). \end{cases}$$

In order to assess "quality" levels, we worked closely with staff at MIT's Lincoln Laboratories, the organization under contract with DOE for technical evaluation, installation and monitoring of photovoltaic experimental and demonstration programs. Lincoln Laboratories' staff identified three categories of PV system failure: (1) lowered array output due to panel degradation, (2) system breakdown, primarily due to power conditioning unit malfunction, and (3) damage to residence through fire resulting from short circuit. Lincoln Laboratories also provided expert judgments for the current rate of incidence of these failure categories (the 1980 column in Exhibit 1a), along with

PV System Operation: Success/Failure Type	Likelihood** (z_i) 1980	1986	Relative Effect* (e_i)
1. Home Damage	0.02	0	− 50
2. Frequent Breakdown	0.50	0.08	− 10
3. Low System Output	0.16	0.00	− 5
4. Works Perfectly	0.42	0.92	1

*Read this as one failure of this type has the same impact on the market as X operating units. Source: Builder Survey (below).

**Read this as 50% of PV arrays installed in 1980 could be expected to break down frequently. Source: MIT-Lincoln Lab Estimates.

EXHIBIT 1A. Likelihood and Relative Effects of Types of PV Residential System Failures.

1. (Home Damage Question): Consider this definition of a failure: Suppose the system actually damaged the residence (through a fire, say) when it failed.

   About how many failures of this kind would *just offset* the positive market impact of *50* successes?

2. (Frequent Breakdown Question): Now, suppose we define failure as a system that broke down frequently (say, once every two–three months) but operated at capacity when it was operating.

   About how many failures of this kind would just offset the positive market impact of *50* successes?

3. (Low System Output Question): Now, suppose we define failure as a system that only supplies 70–80% of its listed output.

   About how many such failures would just *offset* the positive market impact of *50* successes?

EXHIBIT 1B. Builder Survey Questions Used to Assess Relative Effects of Failure Types 1–3 Above.

technological forecasts of how those likelihoods would change by 1986. In our analysis we assumed that the likelihood-of-failure category would change linearly over time from the 1980 numbers to the 1986 estimates and would remain constant at the 1986 figures after 1986.

We performed a telephone survey of 52 builders in the Northeast to assess their perception of the impact on the marketplace (the relative weights—(e_i)) of each of these types of failures relative to the positive effect of a perfectly running demonstration (Exhibit 1b).

In order to estimate the remaining model parameters we used a forecast of photovoltaic sales developed for DOE (Lilien 1982, Lilien and Wolfe 1980).[1] This forecast was developed under the assumption that photovoltaic performance was reliable enough so that reliability was not an issue when comparing photovoltaics with other alternatives. The forecast also assumed, as we do here, that no significant sales will occur before a demonstration program was put in place to eliminate uncertainty

[1]The forecasts were the output of the PV1 model, developed at MIT's Energy Laboratory for photovoltaics planning. PV1 is a comprehensive simulation model of the U.S. market. It includes six sectors (i.e. residential, commercial, etc.) and over 2800 separate geographic and economic planning entities, where for each entity and sector combination decision makers are assumed to choose the systems most appropriate for their needs, given the characteristics they face.

	Cumulative Residential Demand* Forecast (# of Dwellings)***	Price** Per Peak Watt of PV-Installed
1980	0	9.90
1981	4	4.70
1982	243	3.70
1983	497	1.40
1984	835	1.30
1985	1247	1.00
1986	2520	1.00
1987	4877	1.00
1988	7575	1.00
1989	9758	1.00
1990	12104	1.00

*Private purchases only. *Source*: PVI (Lilien and Wolfe 1980) Assuming $1.5 billion federal spending between 1980 and 1986.

**Subsidized price, assuming 40% Federal, 20% State subsidy.

***Assumes 25 demonstrations/year as per DOE plan, as a seed in starting private purchases.

EXHIBIT 2. Base Case Data.

about the performance of the system. The base case data in Exhibit 2 shows the forecast of cumulative residential installations and the net prices (after subsidy).[2]

The model used for this application was:

$$S(t) = X(t) - X(t-1)$$

$$= \left(Ne^{-dp} - X(t-1)\right)\left[\alpha + \beta \sum_{j=1}^{t-1} (X(j) - X(j-1))(1/(1+r))^{t-j-1} \sum_{i=1}^{4} z_i(j)e_i\right] \tag{5}$$

where $N(t)$, the market potential, is taken to be 25 percent of the stock of single family homes (DOE rule of thumb). $N(t)$ was derived from the current Statistical Abstract of the United States and the stock of homes was assumed to increase at 2 percent per year over the planning horizon. The forgetting factor, r, was estimated at 0.1 as a result of interviews with builders and developers. A sensitivity analysis of this parameter is performed below. This model has three parameters now, d, α, and β, that need to be estimated. Using the data from Exhibit 2, and assuming perfect quality as a base case ($z_4(t) = 1$ for all t, all other $z_i = 0$), α, β, and d were estimated using the NBER TROLL system's nonlinear estimation procedure. Exhibit 3 gives the results. Thus, the

Coefficient	Value	Std. Error	t-Stat.
d	5.80**	0.12	49.2
α	0.017	0.016	1.02
β	5.05×10^{-5}*	1.47×10^{-5}	3.43
$R^2 = 0.952$	Corr $R^2 = 0.939$	$F(2/7) = 70.4$	

*Statistically significant at the 0.01 level.

**Statistically significant at better than 0.0005 level.

EXHIBIT 3. Parameter Estimation of Base Case Diffusion Model Using Data from Exhibit 2.

[2]The forecast of the PVI model incorporated the best current information about future market sales, based on extensive market research. While it is not ideal to use forecasts to calibrate models, this source of data was the best available.

parameters d, α and β were estimated under the assumption of "perfect quality", prior to their inclusion in the simulation model, which required, in addition, expert-judgment estimates of the "poor quality" parameters (z_i, e_i and r).

These results were compared with the results of the Bass (1969) model, another 3-parameter model, for fit and predictive ability. Using the same estimation procedure, and data set, the Bass model gave a corrected R^2 of 0.89 (versus the 0.939 reported here), with two of the three parameters significant. In a predictive test of the two models, fitting on the period 1981 to 1985 and predicting 1986 to 1990, the root mean squared error of prediction was 4643 for the Bass model versus 2258 for the model developed here. This model, then, has a prediction error less than half that of the Bass model, even assuming a perfect product.

We use the parameters of this model, together with the estimates about possible negative effects of degrees of PV system failures, to simulate the effect of a demonstration program at any time from 1980 on. Starting a demonstration program at t has the following effects on this model: (1) it switches on R_1 from 0 to α and (2) it adds installations to the installation base.

We ran analyses assuming 25, 50 and 100 PV homes were built by the government in the start year and in subsequent years. (This is referred to as the seed in Exhibit 4b.)

The usual measure of federal program effectiveness is a target—in this case the installation level. While 1990 was the program target year, we ran sensitivity analyses (Exhibit 4a) on that target year, using 1990, 1995 and 2000. In Exhibit 4c we also vary the forgetting factor, from 0.1 to 0.4.

The relative effectiveness measure graphed in these exhibits is *the cumulative number of installations* by the target year, given that installation is *delayed until* t, relative to immediate (1980) installation:

$$\text{Delay Effect}(t) = \frac{X(\text{Target Year; introduce at } t)}{X(\text{Target Year; introduce in 1980})} . \tag{6}$$

Given the results graphed in Exhibits 4a–c, it is clear that a delay until 1986 for start

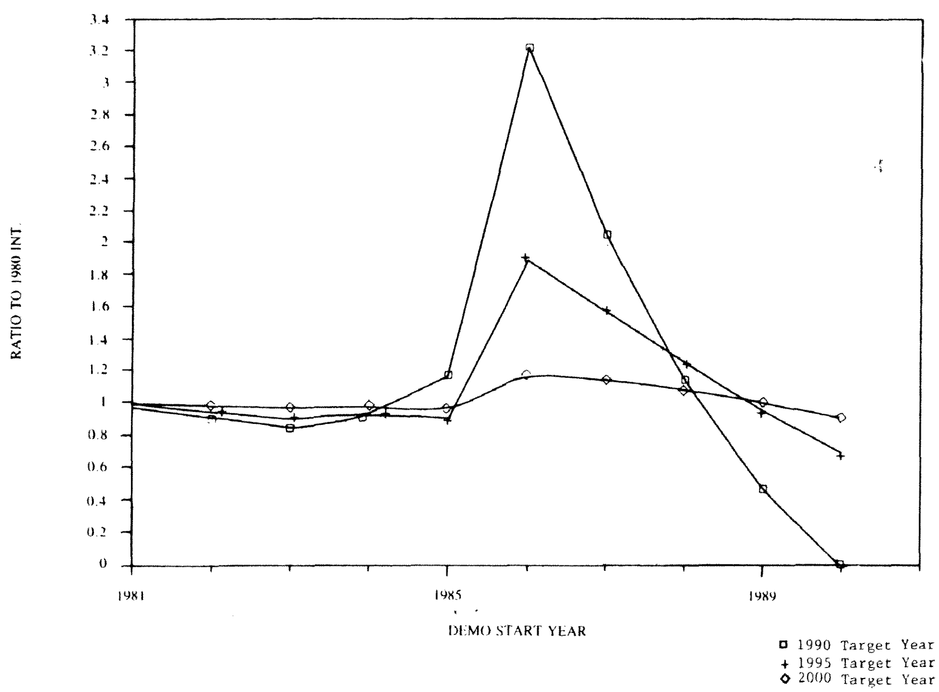

EXHIBIT 4A. The effect of the timing of the start of a PV demonstration program on projected residential penetration: sensitivity on target year. This exhibit suggests that over 3 times as many installations will be in place by 1990 if demonstrations start in 1986 than if they start in 1980.

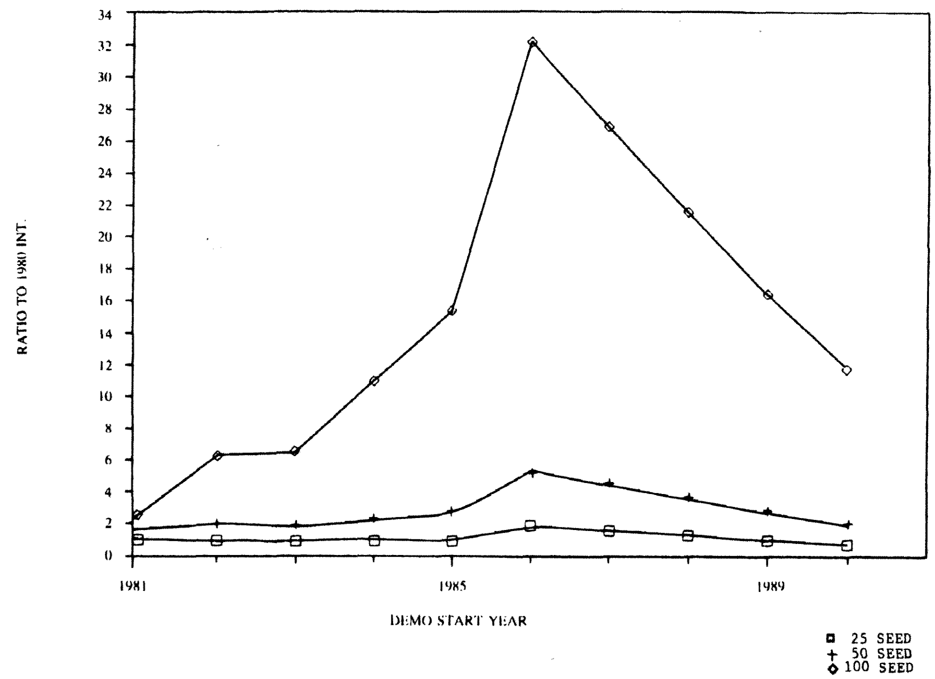

EXHIBIT 4B. The effect of the timing of the start of a PV demonstration program on projected residential penetration: sensitivity on demonstration program intensity (SEED). This exhibit shows that the heavier the intensity of the demonstration program, the worse the effect is of premature market entry.

of the demonstration program seems advisable. Exhibit 4a shows that, with a longer planning horizon, the effect of delay has less apparent impact (because of the forgetting factor). Even for the year 2000 goal, a delay to the year 1986 increases ultimate penetration by *18 percent*.

Exhibit 4b shows that the level of the demonstration program acts as a multiplier of the effect, but does not change the direction of the result. Exhibit 4c shows that r, the

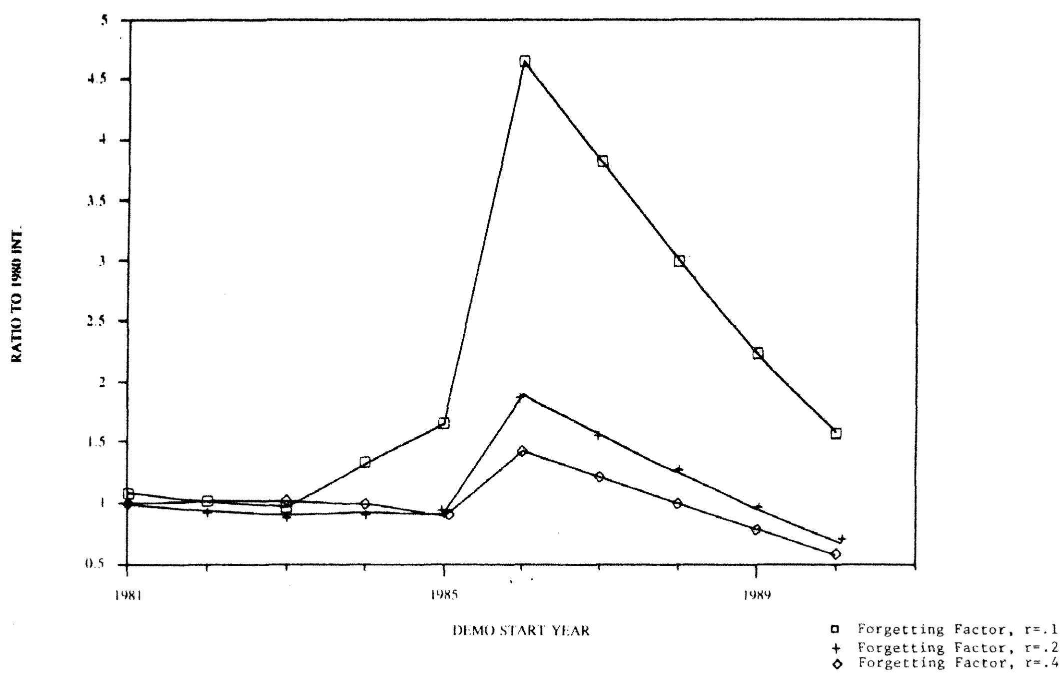

EXHIBIT 4C. The effect of the timing of the start of a PV demonstration program on projected residential penetration: sensitivity on forgetting coefficient, r. This exhibit shows that the effect of premature entry is less critical if the market has a poor memory (r is higher).

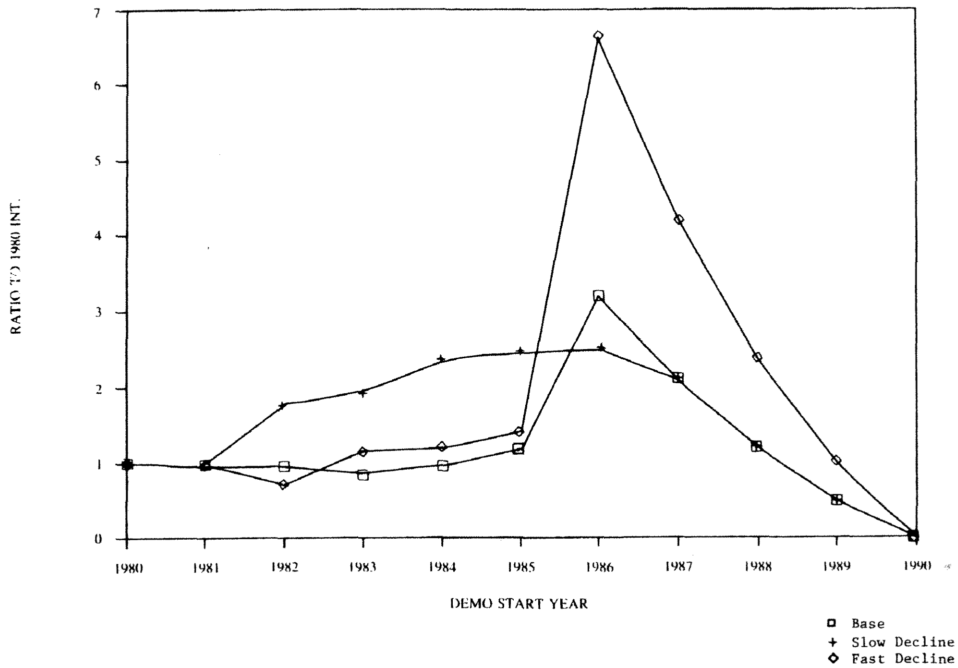

EXHIBIT 4D. The effect of the timing of the start of a PV demonstration program on projected residential penetration: sensitivity on rate of price decline. This exhibit shows that a faster price decline magnifies the negative consequences of premature entry while not shifting the appropriate entry time.

forgetting factor, acts as a damp on the effect. For $r = 0.1$ the effect of past failures is dramatic, for $r = 0.4$, the impacts are lessened. Finally, Exhibit 4d explores the effect of the timing of the price decline on the timing of entry. The "slow decline" shifts all prices in Exhibit 2 two years later (1980 = 9.9, 1981 = 9.9, 1982 = 9.9, 1983 = 4.7, etc.) while the "fast decline" shifts all price declines two years sooner (1980 = 3.7, 1981 = 1.4, etc.). The effect is to magnify the negative consequences of premature entry when prices decline more quickly, without shifting the appropriate entry time.

These results follow clearly from the structure of the model. Until 1986, the marginal effect of a demonstration program ($Q(t)$ in equation (3)) is less than zero. After 1986, $Q(t)$ *is always positive* and under this condition, early introduction is always preferable (Lilien 1980). These results lead to the apparent robustness of the 1986 peak. If the negative effects of word-of-mouth (e_i in Exhibit 1) are lowered by 20 percent, the optimal introduction time becomes 1985.

5. Results and Conclusions

Partly as a result of this analysis, the proposed demonstration program was not funded but was indefinitely delayed. (The dissolution of the photovoltaic program in the Spring of 1981, as the consequence of the Reagan administration's budget cutback, eliminated further follow-up.)

The model and related analysis shows that it is possible to quantify the effects of entry timing on ultimate product success in the market place. It also demonstrates the need to blend various types of data in calibrating such models.

The results presented here have limitations. The expert judgments for the impact of failures and for the rate of quality improvement (Exhibit 1) should be confirmed by an on-going program of market research and product performance monitoring. In addition the model structure looks at the problem from the standpoint of a new technology; there are no competitive elements in the model to permit it to be used in multiple brand markets or where there is threat of future entries. (See Eliashberg and Jeuland 1982 and Yoon and Lilien 1985 for recent work in this area.)

Future model developments could simultaneously consider communication, pricing strategies and timing strategies. Objectives such as maximizing the expected net present value of future profits, not relevant in this application, should also be incorporated in private sector applications.[3]

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