MARKETPLACE COMPETITION IN THE PERSONAL COMPUTER INDUSTRY

Eileen Bridges
Jesse H. Jones Graduate School of Administration
Rice University

Katherine B. Ensor
Department of Statistics
Rice University

James R. Thompson
Department of Statistics
Rice University

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Jesse H. Jones Graduate School of Administration
Rice University
P.O. Box 1892
Houston, TX 77251

Eileen Bridges is Assistant Professor, Jesse H. Jones Graduate School of Administration, Rice University.

Katherine B. Ensor is Assistant Professor, Department of Statistics, Rice University.

James R. Thompson is Professor, Department of Statistics, Rice University; Fellow of the American Statistical Association, Fellow of the Institute of Mathematical Sciences, Fellow of the International Statistical Society, and author of Empirical Model Building; Nonparametric Function Estimation, Modeling and Simulation; Cancer Modeling; Nonparametric Probability Density Estimation.

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ABSTRACT

A decision regarding development and introduction of a potential new product depends, in part, on the intensity of competition anticipated in the marketplace. In the case of a technology-based product such as a personal computer (PC), the number of competing products may be very dynamic and consequently uncertain. We address this problem by modeling growth in the number of new PCs as a stochastic counting process, incorporating product entries and exits. We demonstrate how to use the resulting model to forecast competition five years in advance.

INTRODUCTION

A firm making a decision regarding development of a new personal computer needs to consider many factors including expected demand for PCs and projections of how many PCs will be competing in the intended marketplace at the planned introduction date. At the industry level, annual demand for PCs may be measured as the total unit or dollar sales of PCs in a particular geographic market, such as the U.S. Industry level demand forecasting models are developed in a number of previous works (see [3]). The number of PCs competing for the total industry demand in the U.S. includes all brand names and model numbers available during the year for which the sales are measured, because a customer making a purchase decision in the U.S. will have this number of available options.

If development of a new PC must begin five years prior to its introduction date, a forecast of competition in the marketplace is required five years in advance. A rapidly growing technology-based product category, such as PCs, may appear attractive for new product entries, but if growth declines in the near future, a new product may have difficulty achieving success in a mature market. On the other hand, if the market growth accelerates too rapidly, the product may enter at a time of fierce competition and also have little chance of success. Success in the marketplace depends on continuing steady growth.

Our forecasts of marketplace competition are based on a stochastic counting process model for the number of products, which in this case refers to the number of brands and model numbers of PCs, competing in the market over time. Our model requires only a small amount of relatively accessible data; parameter values may be estimated knowing only the number of PCs on the market for the first few years after introduction of the first PC.

In our model, we consider two primary influences on the introduction of new technology-based products by firms. First, we consider the influence of innovation: Firms develop a new technology internally or purchase it from outside the industry for use in a product, without obtaining the idea from products or firms within the industry. Second, we incorporate the influence of imitation: New products are developed to compete against existing products which are also based on the new technology. Finally, we assess the impact of product exits on the number of products present in the marketplace; we assume that the exit rate is proportional to the number of products on the market.

The results of our estimation indicate that, for the personal computer product class, the rate of product entry depends primarily on imitative behavior. This might be expected in the PC industry, because (1) users of this type of product are not inclined to consider a major break from their present technology due to high switching costs, (2) there is a need for high similarity between products to obtain hardware and software compatibility, and (3) the technology is, in general, easily imitated.

RELATED RESEARCH

The only previous research we have been able to locate which models competition in terms of the number of products on the market is in a paper by Modis and Debecker [10]. These authors deterministically model growth in the number of products based on a new technology over time, incorporating both innovative and imitative influences on product introductions. Product withdrawals from the marketplace are not considered. A deterministic model, such as this, predicts only the expected number of products present in the marketplace over time; it does not take into account uncertainty, which is useful in determining how far from the mean the competitive intensity is likely to stray.

We draw upon stochastic models for technological substitution and sales diffusion in the development of our model. Technological substitution models describe the rate at which firms adopt a new technology to replace an earlier technology. Deshmukh and Chikte [4], Deshmukh and Winston [6], and Meade [9] develop pure birth models for firm adoption of innovation. Deshmukh and Chikte [4] optimize price depending on the number of firms in the industry; their results indicate that, for an oligopoly, the optimal price is lower than the monopolistic price, due to fear of entry. However, if a very large number of firms enter the market, this fear dissolves and the optimal price is the same as in the monopolistic case. Meade [9] incorporates both innovative and imitative influences on the firm's adoption decision; the earlier two papers ([4] and [6]) do not incorporate imitative behavior.

We have also considered work in sales diffusion models, including that of Monahan [11], Böker [2], Tapiero [12], Deshmukh and Winston [5], and Albright and Winston [1]. Monahan [11] and Böker [2] develop stochastic birth-only sales diffusion models for durable products. Monahan's model incorporates both innovative (advertising) and imitative (word-of-mouth) influences on consumer purchases. Analysis indicates that, in the optimal situation, advertising declines after the firm controls over half the market. Monahan [11] also finds that expected profits increase as word-of-mouth (WOM) increases, but the value of WOM lessens as more customers are acquired. Also, as WOM increases, it is optimal to reduce advertising.

Tapiero [12], Deshmukh and Winston [5], and Albright and Winston [1] describe birth-and-death process models for sales diffusion, incorporating the innovative influence of advertising on potential customers. (In these models, births represent increases in market share, while deaths represent decreases.) Deshmukh and Winston [5] optimize the price path for a product over time; analysis of their model indicates that a firm's optimal price increases as its market share increases. Albright and Winston [1] improve upon the two earlier models by considering effects of both advertising and price on market share. Their analysis indicates that optimal advertising increases as market share increases, and although price would be expected to be non-decreasing as market share increases, the authors are unable to obtain this result definitively.

Analyses of the stochastic models described above permitted normative statements regarding the nature of the impact of changes in controllable variables. This type of result is useful, but additional understanding can be obtained by estimating the parameter values in the stochastic models using actual data, and using the fitted model to predict growth. By so doing, we can determine whether the models provide a good fit to reality, and we can use the parameterized version of the model to make predictions, not only of future expected values, but also of variance in the growth process.

MODEL DEVELOPMENT

We developed a model for predicting the number of personal computers (brands and model numbers) competing in the marketplace; our model incorporates product introductions due to both innovative and imitative influences, and product withdrawals from the marketplace. Innovative influences on introduction of new technology-based products include factors not directly related to products already present in the category, such as a high level of in-house R&D activity, low cost of investment in the technology, high expected profitability, and low barriers to market entry. Imitative introduction behavior increases if technology is easily imitated, if R&D commitment of similar firms is low, or if barriers to market entry are high. In addition, the number of products present in the marketplace also depends on the rate of product withdrawals, which is expected to decrease if there are high fixed costs, if the product is an industry standard, or if the product can survive with a low market share.

Growth in number of products over time was modeled stochastically as a counting process. To obtain a stochastic model for product introductions and withdrawals, we incorporated product entry and exit terms, including

$$\lambda_{en} = \lambda_e(N - n) \tag{1}$$

where λ_{en} is the growth rate due to innovative effects, λ_e is a coefficient of innovation (whose units are "per unit time"), N is the maximum possible number of products which may be on the market in the product category, and n represents

$n(t)$, the number of products in the category which are on the market at time t. The growth rate due to imitative effects is given by

$$\lambda_{in} = \lambda_i(n/N)(N - n) \tag{2}$$

where λ_{in} is the growth rate due to imitative effects, λ_i is a coefficient of imitation (whose units are "per unit time"), and N and n are defined as above. The exit or withdrawal rate is modeled as

$$\mu_n = \mu n \tag{3}$$

where μ_n is the product withdrawal rate, μ is a coefficient of withdrawal (whose units are "per unit time"), and n is defined as above.

The Kolmogorov equation for the stochastic model of number of products based on the new technology is given by

$$P_n'(t) = -[\lambda_e(N - n) + \lambda_i(n/N)(N - n) - n\mu]\ P_n(t) + \{\lambda_e[N - (n - 1)] + \lambda_i[(n - 1)/N][N - (n - 1)]\}\ P_{n-1}(t) + [\mu(n + 1)]\ P_{n+1}(t) \tag{4}$$

where $P_j(t)$ represents the probability that there are j products based on the new technology at time t.

As noted by Eliashberg and Chatterjee [7, p.163], (4) cannot be solved analytically. However, we can estimate the parameters of the model using a simulation-based technique.

ESTIMATION TECHNIQUE

The simulation-based estimation (SIMEST) technique of Thompson, Atkinson, and Brown [15] provides a solution to the stochastic model directly from the axioms defining the process, thereby eliminating the necessity of obtaining a closed form solution to a stochastic differential equation. The structure of SIMEST is simple: Given specific parameter values, a realization of the process is simulated from the defining axioms. The proximity of the simulated realization to the observed data supplies a measure of the adequacy of the parameter values used in the simulation. Estimates of the model parameters are then obtained by minimizing the proximity measure over the parameter space.

The axioms of our proposed model are:

A1. The probability a product enters the market in time $[t,t+\Delta t]$ is proportional to both the innovative and imitative entry rates,

$$\lambda_n=[\lambda_e(N-n)+\lambda_i(n/N)(N-n)]\Delta t \quad . \tag{5}$$

A2. The probability a product exits the market in time $[t,t+\Delta t]$ is proportional to the number of products currently on the market; therefore

$$\mu_n=\mu n\Delta t. \tag{6}$$

A3. The probability of two or more occurrences (entries or exits) in $[t,t+\Delta t]$ approaches zero as Δt approaches zero.

Using axioms A1 and A3, it is easily shown that the probability of one entry by time t_e is

$$\begin{aligned} F_e(t_e) &= 1 - P(\text{no entries in time } t_e) \\ &= 1 - \exp(-\lambda_n t_e) \end{aligned} \tag{7}$$

yielding the distribution function of the next entry time. Similarly, for the next product withdrawal time, we have

$$F_w(t_w) = 1 - P(\text{no exits in time } t_w)$$

$$= 1 - \exp(-\mu_n t_w). \tag{8}$$

Because t_e and t_w are continuous random variables, the distribution functions $F_e(t_e)$ and $F_w(t_w)$ are uniformly distributed over the interval [0,1]. The time until the next entry or exit is simulated by generating a random number between zero and one, setting the appropriate distribution function equal to this number, and solving for the time of the event. In equation form, this is

$$t_e = -\ln(u_1)/\lambda_n \quad \text{and} \quad t_w = -\ln(u_2)/\mu_n \tag{9}$$

where u_1 and u_2 are random numbers between zero and one.

We now have a means of simulating the entry and withdrawal times of products in the market. If the generated time until the next entry is less than the time until the next withdrawal, the counting process is increased by one (an entry occurs), while if the time until the next exit is lower, it is decreased by one (a withdrawal occurs). After updating the counting process, new entry and exit times are generated and we repeat the procedure. This procedure is summarized in Figure 1.

INSERT FIGURE 1 ABOUT HERE

When we have obtained our simulated data, we group or "bin" the data by years to correspond with our actual annual observations [15, page 395]. Using the cells of our binning procedure to evaluate the proximity of the simulated data to the observed data, we compute the following chi-squared statistic

k

$$S(\theta) = \sum_{j=1} (\hat{p}_{sj} - \hat{p}_{oj})^2/\hat{p}_{oj} \tag{10}$$

where $\theta = (\lambda, \mu, N)'$ is the vector of model parameters, k is the number of bins, $\hat{p}_{sj}$ is the proportion of simulated observations falling into bin j, and $\hat{p}_{oj}$ is the proportion of observed values falling into bin j.

The simulation-based estimate of θ is given by the value of θ minimizing $S(\theta)$ (see Figure 2). To optimize this function, it is essential that an algorithm uninhibited by noisy data is used. As suggested by Thompson [14], we use the Nelder-Mead optimization algorithm (as discussed in [8]) because of its robustness under conditions of noisy functions.

INSERT FIGURE 2 ABOUT HERE

When we have obtained the parameter estimate , we proceed to estimate its standard error by first generating M realizations of our process at this parameter estimate. We then compute the sample mean of S( ), and sample variance, $s_{S()}^2$, to obtain a measure of the fluctuation of our criterion function, S(). The criterion function is then evaluated over a rectangular grid which has at its center. Using the 95th percentile of the M values of S() as the cutoff for reasonable values of our criterion function, we eliminate all points resulting in other values of $S(\theta)$ from our data set. We then compute the sample variance-covariance matrix for the remaining points. To obtain a confidence region for θ, we approximate the distribution of by a multivariate normal distribution with mean and variance-covariance matrix given by the sample matrix computed above.

MODEL APPLICATION

The data used in this study includes the number of personal computers (identified by brand and model number) introduced during the years 1972 through 1988; a total of 749 personal computers are represented, from 190 firms.[i] Of the 749 PCs introduced, 320 were withdrawn from the market during the time of the study.

The SIMEST algorithm described above was used to estimate stochastic model parameters for the personal computer data. The results, reported in Table 1, indicate that imitative influences on growth in number of personal computers have considerably greater impact than do innovative influences.

Table 1: Results of Parameter Estimation

PARAMETER	ESTIMATE	STANDARD ERROR
λ_e	0.00060	0.00009976
λ_i	0.5155	0.08651
μ	0.05596	0.007153
N	515.0	63.79

Using these parameter values to fit estimates to the actual growth data, we obtain a mean absolute deviation (MAD) of 7.18, and a mean squared error (MSE) of 193.18. Our parameter estimates indicate that the rate of entry due to imitative factors and the exit rate both have a significant impact on the number of PCs present in the marketplace. However, in the early stages of the growth process, introductions dominate withdrawals due to the multiplicative impact of potential in the marketplace. The actual introduction rate may be higher than that represented by our growth factors; product introductions and withdrawals may cancel each other in our net change data, resulting in lower values for both parameters in our estimation of the model. This is a topic worthy of further investigation.

We used the parameter values obtained via the SIMEST procedure (as reported in Table 1) to estimate growth in the number of models of personal computers. The resulting estimated and actual growth curves are plotted in Figure 3. Our forecast indicates that the number of models of PCs on the market will peak in 1992.

INSERT FIGURE 3 ABOUT HERE

To evaluate the stability of S(), we performed 500 simulations of the process using the parameter estimates given earlier. The resulting mean and standard deviation of S() are 8.62 and 0.823, respectively. A histogram of S() for the 500 simulations is given in Figure 4.

INSERT FIGURE 4 ABOUT HERE

To validate our model's usefulness to a personal computer product manager in predicting competition in the marketplace at the time of a planned introduction, we assumed that in 1983 a decision had to be made regarding the 1988 introduction of a new personal computer. Therefore, based on data through 1983, we obtained a prediction as to the expected degree of competition in the marketplace in 1988.

To make this prediction, we estimated our stochastic growth model, using only the data for number of products on the market during the period 1972-1983. Because we had fewer data points available for this estimation, and because λ_e was so close to zero in our analysis of the entire data set, we set $\lambda_e=0$ for this estimation. We then applied SIMEST to obtain estimates of the other parameters; the results were $\lambda_i=0.50$, $\mu=0.055$, and N=500.

Using these parameter estimates, we simulated the empirical distribution of the expected number of products present in 1988, based on observations through 1983. We considered two sources of variation in obtaining this distribution. First, there is inherent variation in SIMEST; in other words, there is variation in the comparison function S() at any given point in the parameter space. To evaluate this uncertainty, we generated 1000 realizations of our criterion function at the parameter values given above, yielding a 95th percentile value for S() of 4.76. Our second source of variation is due to uncertainty present in our parameter estimates. We simulated the process at points in the neighborhood of the parameter estimates, and then used the 95th percentile of S(), 4.76, as a cutoff point; thus, all parameter values for which S() was greater than 4.76 were eliminated from the data set. By doing this, we obtained a set of possible values for θ which are in the neighborhood of . We then computed the sample variance-covariance matrix for this set of possible values for θ.

To simulate the distribution for expected number of products present in 1988, we generated 1000 sets of parameter values using a multivariate normal distribution with mean given by our parameter estimates and the variance-covariance matrix described above. At each set of parameter values, we simulated the number of products present in 1988 ten times, yielding a total of 10,000 simulated values. A histogram of the resulting empirical distribution of number of PCs on the market in 1988 is provided in Figure 5.

INSERT FIGURE 5 ABOUT HERE

MANAGERIAL IMPLICATIONS

A product manager's decision regarding introduction of a new personal computer depends, in part, on the number of competing brands (and model numbers) expected on the market at the time of introduction. Based on a steady increase in the number of personal computers on the market between 1983 and 1988, the manager would have expected to face about 400 competitive PCs in 1988. If growth had slowed dramatically between 1983 and 1988, the product would have been introduced into a mature market, reducing the likelihood of success. If market growth had accelerated rapidly during this time period, competition may have been too intense by 1988. To be reasonably sure of entering a steady growth market, the manager might have set a minimum threshold (e.g., do not introduce the product if the probability is too great that there will be fewer than 350 PCs on the market in 1988) as well as an upper limit for entry (e.g., do not introduce the product if the probability is too great that the number of competitors will exceed 450). Given the empirical distribution derived above, the probability of the number of 1988 competitors being between 350 and 450 is 67.7%. Therefore, based on personal experience and knowledge of the industry, the manager would have made a decision as to whether this probability was acceptable.

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

We have presented a stochastic counting process model for growth in the number of products on the market which incorporate a technological innovation, and have estimated parameter values for this model using a recently developed procedure called "SIMEST." We have applied this model to data regarding the number of brands and model numbers on the market in the personal computer industry; we have obtained an excellent fit to actual data, and have also demonstrated the use of the technique for forecasting the market five years in advance.

Our further research in this area will include modeling of the interaction between expected industry demand and expected number of competing products (brand names and model numbers for PCs) on the market. We anticipate that sales for products based on a new technology will reach a peak as the market becomes saturated, and that following this peak, the number of competitors will also decline.

FOOTNOTE

i. Our data were drawn from an industry survey by InfoCorp.

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