New technology adoption in an innovative marketplace: Micro- and macro-level decision making models

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Abstract: Innovative markets are those which are undergoing rapid development due to changing customer needs or improving technological capability. Because these markets are so dynamic, new products are introduced frequently, and there is a high degree of uncertainty regarding their potential for success. We review literature relevant to firm decision-making, including such topics as timing the adoption of a technological innovation, determining optimal spending on an innovative technology, and predicting the success of a class of products which are based on a particular innovative technology. We consider these problems both at the micro (individual firm) and macro (aggregate) levels.

Keywords: Innovation, Diffusion, Technology, Adoption

A major means of competition in capitalistic economics is the introduction of innovations, some of which carry with them substantial profits. Successful innovations represent improvements over existing alternatives, replacing older products through a process of ‘creative destruction’. Over time, then organizations which do not innovate will not be able to compete [Schumpeter (1942)]. This process is accelerated in ‘innovative markets’, i.e. product markets where the rate of commercialization of innovations is high. Our focus is on such markets, and in particular, on the desirability and timing of adoption of new technologies in these markets.

Innovative markets are characterized by change and uncertainty. Early models for adoption of innovation generally represented the marketplace deterministically, and made their recommendations based on assumptions of certainty. Although more recent models incorporate dynamic effects (such as learning) and risk, their recommendations to the decision maker have not changed dramatically. Rather, they elaborate on and improve the earlier models, and provide understanding of additional variables.

There are other literature reviews which cover topics included in this survey. Kamien and Schwartz (1982) and Reinganum (1989) describe

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models for firm adoption of innovation, and Gatignon and Robertson (1988) discuss organization adoption decisions in a competitive environment. Mahajan, Muller and Bass (1990) provide an extensive review of deterministic models for diffusion of innovation; Kalish and Sen (1986) discuss the impact of marketing mix variables on diffusion. Stochastic models for innovation diffusion are reviewed by Eliashberg and Chatterjee (1986).

Our survey differs from previous reviews in that we address timing of new technology adoption both at the micro (individual firm) level and at the macro (aggregate) level. We first discuss models which aid individual firms in decisions regarding innovation adoption and the timing thereof. Next, we consider aggregate sales models which predict marketplace behavior. These two levels of adoption behavior are actually interdependent: firm decisions may be aggregated to estimate overall market growth, but predictions of market growth are useful to each individual firm in deciding upon its strategy. Therefore, we suggest future research developing models to describe this micro- and macro-level interdependence, and using the results to make normative recommendations.

1. The individual firm adoption decision

A new technology available to a firm may be an industrial 'process' innovation, providing improvement to the production process, or a 'product' innovation, which may be incorporated into a product or service. For example, Hewlett-Packard (HP) may wish to incorporate a new integrated circuit technology into a microprocessor chip for personal computers (PCs). If the major benefit obtained from use of the technology is a reduction in production costs, we say that HP is considering adoption of a process innovation. If the primary benefit is a faster PC, HP would be adopting a product innovation. We use the term ‘adoption’ in Part 1 to denote the time at which a firm begins using an innovative technology. The first firm to adopt a new technology is called an ‘innovator'; we occasionally refer to later adopters as ‘imitators’.

Firms considering use of a new technology must decide whether and when to adopt. In general, this involves comparing the present value of expected benefits of innovation to the present value of the cost. A complicating factor is that an innovation may be available for purchase (and have a known present value of cost), or it may be developed by the adopting firm, requiring some flow of expenditures during an uncertain development period (so the present value of cost is not known).

Part 1 of this review describes models designed to aid in the firm’s decision regarding adoption of a new technology. Some of the topics included are timing of the adoption, optimal expenditures for either purchase of an innovation or a flow of development costs, and comparison of multiple future innovations.

1.1. Timing of firm innovation

A number of researchers, particularly in the economics literature, have addressed the problem of individual firm timing of innovation adoption. If the decision is modeled deterministically, a firm need only consider known future events in deciding whether and when to adopt a new technology. For example, Barzel (1968) develops a decision theoretic model which compares the present value of cost savings (or profit gains) to the present value of the investment required to obtain the innovation. In this model, the net present value (NPV) is the difference between anticipated cost savings and investment cost:

$$NPV = \frac{kX_0 e^{-(r-p)t}}{r-p} - I e^{-rt} \quad \text{for } r > p,$$

where

- $k$ = cost savings per unit of product manufactured,
- $X_0$ = demand for the product at time 0,
- $p$ = growth rate of demand,
- $r$ = discount rate,
- $I$ = investment cost required to obtain the technology.

Solving for the optimal time of innovation adoption, Barzel obtains:

$$t_{opt} = \frac{\ln(r) + \ln(I) - \ln(kX_0)}{p} \quad \text{for } r > p.$$
If \( t_{\text{opt}} \) is replaced into the original expression for \( NPV \), the results indicate that the optimal time of adoption occurs when the present value of investment cost is equal to the present value of production cost savings. Thus, the optimal adoption time balances the cost of earlier adoption and the cost of producing without the innovation. This optimal adoption time is earlier if there are decreases in the required investment or in the discount rate (either of which leads to decreases in adoption cost), or if there are increases in initial demand, growth rate of demand, or cost savings per unit.

Barzel's deterministic model does not allow for the probabilistic effects of competition on the individual firm's adoption timing decision. Kamien and Schwartz (1972) extend his model such that if the firm is first to adopt the new technology, rewards are greater than if the firm adopts after at least one competitor has adopted. To do this, their model for production cost savings (or increased revenue) incorporates a 'composite rival,' represented by a probability distribution over possible dates for rival adoption. Production cost savings (or additional profit contribution) are assumed to be greater for the firm which adopts earlier. Investment costs are modeled as being independent of the firm's status as first or later adopter. Similar to Barzel, Kamien and Schwartz conclude that the firm's adoption time should be earlier if the rewards for first adoption increase, or if the rewards for later adoption decrease. They also note that if the probability of early rival adoption increases, the firm should innovate earlier.

**Summary:** The optimal adoption time is earlier for lower investment costs, higher expected profits, lower rewards for later adoption, or a higher probability of early rival innovation.

**Example:** One example of differences in adoption timing is the speed at which retailers begin stocking various types of products. Consider, for example, department stores which sold both Cabbage Patch dolls and home computers. There was good reason for Cabbage Patch dolls to be adopted into a store's line more quickly than home computers: the dolls required a much smaller investment to sell successfully (because sales personnel did not need special training); also, there was a large proven market for the dolls, while there was doubt as to the size of the home computer market. Thus, Cabbage Patch dolls were characterized by a lower cost of adoption than home computers, and they also offered a high initial demand.

### 1.2. Optimal R&D expenditures for innovation

If a firm develops an innovative technology in-house (as opposed to purchasing the technology), the investment cost is not incurred at a single point in time, but instead requires a stream of expenditures. In this case, the expenditure per period influences the timing of innovation: higher rates of investment are expected to lead to earlier innovation. The optimal investment in an innovation is critically dependent on whether the model assumes that the innovation is purchased with a one-time investment or with a flow of development expenditures which may be curtailed immediately upon rival innovation.

Assuming a flow of development costs, Kamien and Schwartz (1978) use a decision theoretic model to determine a firm's optimal expenditure plan as a function of time. They assume an expected profit stream that depends on relative timing of the firm's innovation and rival innovation (which is assumed to follow a probability distribution). Their analysis indicates that as the number of competitors increases, a rival innovation is expected earlier, and the firm's optimal investment rate increases, in order to obtain an earlier innovation. Also, a firm which has the only currently successful technology will not be motivated to innovate unless threatened by the possibility of rival innovation. If a rival does enter the market, leading to severely decreased rewards, investment may slow or cease; however, if rewards for imitation are large enough, investment may increase upon rival innovation.

Because earlier models assume a probability distribution for rival innovation, Loury (1979, p. 396) notes that 'R&D strategies chosen by other market participants ... cannot be treated as a parameter'. To avoid forcing rival response into a prespecified distribution, Loury develops a game-theoretic model for \( n \) identical firms, in which he treats innovation as a stochastic function of R&D investment; thus, the firm's innovation time and rival innovation times are both uncertain. In this model, investment costs and profits due to successful (i.e. first) innovation are given as the present value of infinite flows, and
later adopters receive no reward. Thus, in contrast to Kamien and Schwartz, he models investment cost as a one-time expenditure. This leads to the opposite result regarding the optimal investment strategy: as the number of competing firms increases, the optimal investment per firm decreases. Lee and Wilde (1980) use a model similar to Loury's, but instead of modeling R&D investment as a one-time cost, they allow for both a fixed cost and a continuing flow of expenditures. Their results agree with those of Loury and of Kamien and Schwartz, in that if both fixed and flow costs are incurred, whichever has the larger present value dominates the other in determining the effects of number of competing firms on investment strategy.

Reinganum (1981a, 1982) obtains a similar R&D spending plan using a more general game theoretic model. In her research, rival firms compete to be the first to innovate; perfect patent protection is assumed, so that only the first adopter receives rewards. Timing of the innovation is modeled as a stochastic random variable whose distribution improves (likelihood of innovation increases) as R&D expenditures increase. The model incorporates uncertainty both in the expenditures required for innovation and in the date of rival innovation. Reinganum's optimal R&D spending path indicates that perfect patent protection leads to increases in innovative activity, while increasing likelihood of R&D imitation and rewards for imitation lead to decreases in innovative activity. These results are consistent with those of Lee and Wilde because development costs are modeled as flow costs; if one-time expenditures were used instead, increasing rivalry would lead to lower investment in R&D, similar to the result obtained by Loury.

Summary: If the firm's investment requires a one-time expenditure, then the optimal investment is larger when there is a smaller probability of rival innovation. If the investment requires a flow of expenditures, and a rival has not yet innovated, then the optimal rate of investment is larger when there is a higher probability of rival innovation, when patent protection increases, and when rewards for imitation decrease. If the investment requires a flow of expenditures and a rival has already innovated, the optimal rate of investment is larger if rewards for imitation increase.

Examples: As an example of a one-time R&D investment, consider the City of Houston's request for proposals to develop a light rail system. Several firms have submitted designs and bids for construction of the system. The 'winner' will be the firm which receives the contract; this firm will obtain the rewards accruing to the first innovator. Theoretical results suggest that to encourage the greatest possible R&D investment from each competitor, it may have been optimal for the City to limit the number of rivals permitted to submit proposals. Without this restriction, firms may not have incentive to invest a sufficient amount in the proposal preparation, due to the low probability of winning the contract.

As an example of R&D investments requiring a flow of expenditures, consider the development of semiconductor components. Computer memory chip (DRAM) design offers a considerable reward for imitation: although the first firm to introduce a 16 megabit DRAM is expected to reap the greatest rewards, firms which enter the market later are still expected to make a profit. The design of microprocessors is more of a 'winner takes all' proposition. When Intel introduced the 80386 in 1985, it was the most powerful microprocessor on the market and was compatible with Intel's earlier models, but it was not covered under previous licensing agreements with other manufacturers. Intel protected the design and was able to be the sole supplier of the 80386, thus obtaining full rewards of innovation.

1.3. Incorporating uncertain rewards to innovators

Some of the models described thus far make timing of innovation a stochastic function of R&D spending. However, none of the above models incorporates the effects of uncertain profitability on timing of innovation adoption. Reinganum (1983) allows for uncertain rewards to innovators and finds that the higher a firm's costs are for using the current technology, the more likely that firm is to innovate. This conclusion is plausible, because less is at risk if current costs are high.

Jensen (1982) also incorporates uncertain profitability, by assuming that a firm has a prior probability regarding the profitability of an innovation, which is revised indefinitely until a threshold probability is reached. The results indicate that firms should adopt an innovative technology
earlier if there is an increase in the expected profitability, or a decrease in the adoption cost or the discount rate. McCardle (1985) extends Jensen's model, making it more realistic by assuming a cost of delaying adoption and continuing to gather information. In addition, McCardle assumes two thresholds, defined as follows: if the probability that an innovation will be profitable exceeds the upper threshold, the firm should adopt, while if this probability crosses the lower threshold, the technology should be permanently rejected. Analysis of the model indicates that an increase in information cost or a decrease in the discount rate leads to a more rapid decision.

Another approach to stochastic modeling of innovation costs and rewards is offered by Mamer and McCardle (1987). In this game theoretic model, technological development and competitive activity are both modeled stochastically. Each firm is assumed to have a prior estimate of an innovation's profitability, and to gather more information regarding this profitability. Following Bayesian updating of the profitability estimate, a firm may adopt the innovation, reject the innovation, or continue to purchase information. In the analysis of this model, if a competitive firm is likely to introduce a (similar) substitute product, the firm should be less inclined to adopt, while if a complementary product is likely, the firm should be more inclined to adopt. These results are consistent with those obtained earlier for investment requiring a one-time expenditure.

**Summary:** When rewards are uncertain, optimal firm adoption timing results are consistent with those obtained when rewards are assumed known.

1.4. What if more than one innovation is available or expected?

The models discussed to this point can be used to determine optimal timing of firm investment in a particular innovation (given assumptions), but if multiple innovations are available or expected, the decision is more difficult. In this case, a selection must be made among the alternatives, and timing of the investment(s) optimized.

When multiple innovations are available simultaneously, a firm may compare all of the alternatives and select the best one. Jensen (1983) assumes that a firm must select one of two available innovations; a prior probability is updated until sufficient information gathering eventually leads the firm to select the better innovation. A more realistic approach to multiple innovations is suggested by Balcer and Lippman (1984). If a firm expects a stream of innovations, a decision must be made to either adopt the best current technology or to postpone adoption. If a firm decides to tolerate a certain degree of technological 'gap' between its own technology and the best currently available technology, adoption will not occur until the gap exceeds this threshold. Higher expectations regarding future innovations lead to a higher threshold and consequently, later adoption. An implication of this result is that an existing technology which was previously rejected may be adopted, if an expected advance does not occur, because the lack of this advance leads to a reduction in expectations. Another important implication is that increased uncertainty does not necessarily lead to slower adoption: it implies a wider spread of expectations and consequently a wider range of adoption times (both earlier and later than previously).

Weiss and John (1989) develop a similar adoption time decision model, incorporating uncertainty, belief updating, technological obsolescence, switching cost, and technological expectations. Their model allows three possible decisions, including adopting, waiting for more information, or 'leapfrogging', which is defined by the authors as a decision to wait for the next technological generation before adopting. Analysis of the model indicates that adoption is more likely for firms having a large technological gap, while leapfrogging is more likely for firms expecting greater technological improvements and/or earlier introductions of these improvements.

**Summary:** A firm making a decision among a stream of innovations is more likely to postpone adoption if it has higher expectations of future developments or if its current technology is more advanced.

**Example:** The situation in the steel industry which faced U.S. and Japanese steel producers at the end of World War II is an example of how adoption speed depends on technological gap. Japanese steel production facilities had all been destroyed, so their technological gap was immense. The Japanese quickly adopted the latest production technology, while U.S. producers did
## Exhibit 1
### Individual firm adoption decisions.

<table>
<thead>
<tr>
<th>Author/Date</th>
<th>Model Type</th>
<th>No. of Firms in Market</th>
<th>Type of Expenditure for Innovation</th>
<th>Any Rewards to Imitators</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barzel (1968)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time</td>
<td>None</td>
<td>Innovations should be adopted earlier if there are decreases in the required investment or in the discount rate, or if there are increases in initial demand, growth rate of demand, or cost savings per unit.</td>
</tr>
<tr>
<td>Kamien and Schwartz (1972)</td>
<td>Decision theory</td>
<td>2 (one firm is a 'composite rival')</td>
<td>One-time</td>
<td>Reduced as compared to first adopter</td>
<td>Innovations should be adopted earlier if the probability of rival innovation increases or if the rewards for innovating increase. Innovations should be adopted later if the probability of rival imitation increases, or if the rewards for imitating increase.</td>
</tr>
<tr>
<td>Kamien and Schwartz (1978)</td>
<td>Decision theory</td>
<td>2 (one firm is a composite rival)</td>
<td>Flow</td>
<td>Reduced as compared to first adopter</td>
<td>Increases in competition lead to increases in optimal investment in innovation. Monopolists with little threat of rival innovation have little motivation to invest in development of new technology.</td>
</tr>
<tr>
<td>Loury (1979)</td>
<td>Game theory</td>
<td>n</td>
<td>One-time (present value)</td>
<td>None</td>
<td>Increases in number of competitors (n) lead to decreases in per firm R&amp;D investment.</td>
</tr>
<tr>
<td>Lee and Wilde (1980)</td>
<td>Game theory</td>
<td>n</td>
<td>One-time plus flow</td>
<td>None</td>
<td>Increases in number of competitors (n) lead to increases in per firm R&amp;D investment, if this investment is primarily a flow of expenditures.</td>
</tr>
<tr>
<td>Reinganum (1981a)</td>
<td>Combines game and decision theory</td>
<td>2</td>
<td>Flow</td>
<td>None</td>
<td>No unambiguous results are obtained, due to complexity of the process.</td>
</tr>
<tr>
<td>Reinganum (1982)</td>
<td>Combines game and decision theory</td>
<td>n</td>
<td>Flow</td>
<td>None</td>
<td>Perfect patent protection, low probability of imitation, and low rewards for imitation lead to increases in innovative activity.</td>
</tr>
<tr>
<td>Reinganum (1983)</td>
<td>Game theory</td>
<td>2</td>
<td>One-time</td>
<td>None</td>
<td>The higher a firm’s current costs are, the more likely that firm should be to innovate.</td>
</tr>
<tr>
<td>Jensen (1982)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time</td>
<td>None</td>
<td>Firms should adopt innovative technology earlier if there is a decrease in the adoption cost or an increase in the discount rate or the expected profitability.</td>
</tr>
<tr>
<td>McCordle (1985)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time plus flow</td>
<td>None</td>
<td>Firms should gather less information prior to an adoption decision if the cost of search increases or the discount rate decreases.</td>
</tr>
<tr>
<td>Mamer and McCordle (1987)</td>
<td>Game theory</td>
<td>2</td>
<td>One-time plus flow</td>
<td>Yes</td>
<td>Firms should be less willing to adopt if the profitability of a competitive substitute increases, and more willing if the profitability of a competitive complement increases.</td>
</tr>
<tr>
<td>Jensen (1983)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time</td>
<td>None</td>
<td>By gathering information and updating priors, firms may optimize a choice between alternate innovations. This decision depends on the nature of the information collected and on characteristics of the firm.</td>
</tr>
<tr>
<td>Balcer and Lippman (1984)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time</td>
<td>None</td>
<td>Firms tolerate a certain degree of technological &quot;gap&quot;; they adopt a new technology when the current technology exceeds this threshold. Higher expectations regarding future innovations lead to a higher threshold and consequently, later adoption.</td>
</tr>
<tr>
<td>Weiss and John (1989)</td>
<td>Decision theory</td>
<td>1</td>
<td>One-time</td>
<td>None</td>
<td>Adoption is more likely for firms having a large technological gap; leapfrogging is more likely for firms expecting greater technological improvements and/or earlier realization of these improvements.</td>
</tr>
</tbody>
</table>
not upgrade their facilities. As a result, U.S. steel producers fell from their leadership position.

1.5. Conclusions regarding firm adoption decision models

The models reviewed in Part 1, for predicting timing of firm adoption of innovation, are theoretically interesting and provide intuitively satisfying normative results. However, the predictive variables used in these models are not generally available to marketplace decision makers. Luke-warm generic variables such as ‘high rewards to imitators’ are used in place of variables measuring fundamental market forces which influence actual firm decisions regarding timing. For example, rewards to imitators may be high if the first firm to innovate underestimates demand, if demand is segmented such that specialized entries targeted at particular market niches are expected to be profitable, or if reverse engineering allows a product with identical benefits to be produced at low cost without patent infringement.

Perhaps because of this incomplete mapping from the model variables to real-world fundamentals, the theoretical models described in this section are generally not subjected to empirical testing. Testing this type of model on marketplace data would increase credibility for the design of the model and provide confirmation of the recommendations which stem from the analysis.

A summary of the firm adoption models discussed in this section is provided in Exhibit 1.

2. Prediction of aggregate sales

Although the economics literature addresses modeling the timing of firm adoption of innovation, these models generally require a forecast of profits which will accrue following adoption. Whether the innovation reduces production costs or enhances the value of a product, the amount of profit due to the innovation depends on sales. Thus, to make an estimate of future profits, the firm needs to be able to forecast industry sales of the product over time.

In this section, we first discuss models which forecast aggregate sales as a new product diffuses into a homogeneous target market. Next, we consider recent models which include individual differences, either by assuming a heterogeneous target population described by a probability distribution, or by aggregating the results of individual level adoption decision models. In Part 2, we use the term ‘adopter’ to describe a purchaser of a product, whether this purchaser is a firm or a consumer. We use the words ‘innovative’ and ‘imitative’ to describe influences which affect a purchase decision: when a purchase is made due to imitative influences, information from previous purchasers (called ‘word-of-mouth effects’) impacts the decision, while if a purchase is innovative, this is not the case. There is, however, some overlap, because both influences may act in a purchase decision.

2.1. Aggregate level diffusion models

Diffusion models, which predict sales as a function of time, are commonly found in the marketing literature, although a few key papers are from economics. A large body of literature in marketing deterministically models the behavior of the target market at the aggregate level. Later models have incorporated uncertainty by making the models stochastic; however, very few of these have been developed, probably because they are difficult or impossible to solve analytically.

The simplest diffusion models assume that a fixed total potential market (or target population) exists for an innovation, and that each purchaser buys the innovation only once. The cumulative number of purchasers is modeled to approach this total potential (or some known fraction of it) as time passes.

One of these simple diffusion models is an ‘external influence’ model, which considers only influences outside the adopting population in predicting how many of the remaining potential market members will purchase during a particular time period. External influences include advertising, promotion, price, and distribution. An example of this type of model is that described by Fourt and Woodlock (1960), which has the form

\[ Q(t + 1) - Q(t) = a[M - Q(t)], \]

where

\[ Q(t) = \text{the cumulative number of adopters at time } t, \]

\[ a = \text{the 'coefficient of innovation', a constant which indicates how likely members of the} \]

E. Bridges et al. / New technology adoption models 263
target population are to innovate (given a constant set of external influences),

\( M \) = the maximum total number of adopters.

In this model, the number of potential adopters who have not purchased by time \( t \) is given by \([M - Q(t)]\).

Another simple diffusion model is an 'internal influence' model, which considers only influences within the adopting population in predicting purchases among the remaining members of the potential market. These influences include such effects as word of mouth. Examples of this type of model are those of Mansfield (1961) and Fisher and Pry (1971), which have the form

\[ Q(t+1) - Q(t) - \left( \frac{b}{M} \right) [Q(t)][M - Q(t)] \]

where

\( b \) = the 'coefficient of imitation', a constant which indicates how likely members of the target population are to imitate previous adopters in their adoption decision.

Blackman (1974) extends the internal influence model such that products based on a new technology replace those based on an older technology; he predicts market share for the new technology as a function of time. He notes that the rate of substitution of a new technology depends not only on its profitability and investment cost, but also on the nature of the industry. More innovative industries are generally more competitive and dynamic; they tend to be those which produce durable products, including aircraft, electrical machinery, and communication devices.

Less innovative industries tend to produce non-durable products, such as paper, rubber, and textiles.

A generalized diffusion model, which combines the effects of external and internal influence, is suggested by Bass (1969). His model takes the form

\[ Q(t+1) - Q(t) - a[M - Q(t)] + \left( \frac{b}{M} \right) [Q(t)][M - Q(t)] \]

where the variables are defined as they were previously. Bass applied this model to eleven consumer durable products, and was able to obtain good fits to actual data as well as successful prediction of sales growth for color television.

2.2. Enhancements of aggregate level diffusion models

A number of improvements have been made to aggregate level diffusion models, to allow consideration of the impact of additional variables (such as marketing mix, changes in the potential market, and replacement purchases) on the diffusion of an innovation. For example, Horsky and Simon (1983) include effects of advertising in a Bass-type diffusion model for sales of banking services. They note that increasing advertising leads to greater external effects relative to internal effects; consequently, advertising for a new product should optimally start high and decrease gradually.

Another enhancement of a sales diffusion model relaxes the assumption of a fixed total potential adopter population. For example, Mahajan and Peterson (1978) modeled sales of washing machines in the United States from 1950 to 1974. They used a generalized Bass-type model, with a dynamic potential market proportional to the number of housing starts during that time period. By allowing for a dynamic adopter population, the model obtained a significantly better fit to actual data, indicating that size of the potential market may impact diffusion. For additional information on this topic, see Bass (1980), Horsky (1990), Kalish (1985), or Sharif and Ramanathan (1981).

Defining a portion of sales as replacements (based on age of the products which have been sold and their expected life) has improved the performance of sales diffusion models [Kamakura and Balasubramanian (1987); Lilien, Rao, and Kalish (1981); Mahajan, Wind, and Sharma (1983); Olson and Choi (1985); Rao and Yamada (1988)]. Further improvement would be expected if multiple purchases for simultaneous use were considered separately.

Norton and Bass (1987) also segment purchasers, in a model for sales diffusion of integrated circuits based on sequential generations of technologies. Each technological innovation may be adopted by new users, and may attract a percentage of the market which has already adopted earlier technologies. A key assumption is that there is a constant per user per period average consumption, and that sales growth comes through an increase in the number of users. This
assumption is believable for the integrated circuit industry, and the model obtains good fits to actual sales peaks. However, the model may not be generalizable to other industries.

Sales diffusion in the presence of supply restrictions is modeled by Jain, Mahajan, and Muller (1991), following the work of Simon and Sebastian (1987). Both papers use data from monopolistic telephone companies; the former uses Israeli data and the latter uses German data. Jain et al. confirm a Simon and Sebastian finding that supply restrictions cause the diffusion curve to be negatively skewed (i.e. to have a slow growth rate and a rapid rate of decline). In addition, they show that an optimal marketing mix policy generally includes monotonically decreasing advertising and monotonically increasing distribution, with advertising starting prior to distribution. This result occurs because it is costly to make the product available, so advertising first creates a queue of applicants who will adopt immediately upon availability. Interestingly, in their empirical analysis, Jain et al. show that these waiting applications tend to generate negative word-of-mouth, reducing the positive internal effects on diffusion due to word-of-mouth from previous adopters.

Summary: Both fits and forecasts obtained using diffusion models are improved by incorporating the effects of marketing mix variables like advertising, economic fundamentals like housing starts, and product characteristics like replacement propensity. External constraints on normal diffusion, such as supply restrictions, can overturn some accepted intuition from the basic model as well.

2.3. Stochastic sales diffusion models

A few aggregate level stochastic diffusion models have been developed. Some of these are structurally stochastic, representing diffusion itself as a stochastic process. Tapiero (1983) models movements of target customers from unaware to aware to purchasing as a stochastic Markov process (having non-stationary transition probabilities). He describes methods for estimating parameters of this model under very general conditions; for example, the model may be modified to incorporate a dynamic potential adopter population or a heterogeneous target market. Although a general analytical solution cannot be obtained, the results of this model provide a better understanding of the impact of external and internal influences on adoption behavior: for example, Tapiero finds that advertising may increase word-of-mouth activity among aware potential buyers. Böcker (1987) develops a model similar to that of Tapiero, but uses a counting process approach rather than a Markov process to stochastically model adoption of an innovation by members of a target population.

Aggregate level models may instead be parametrically stochastic, incorporating stochasticity into the parameters of the model. For example, Lilien, Rao and Kalish (1981) incorporate five stochastic parameters into their repeat purchase diffusion model. Eliashberg, Tapiero and Wind (1987) model the coefficients of innovation and imitation in the Bass (1969) diffusion model as stochastic parameters. They observe that the temporal pattern for the stochastic model is always below that for the deterministic model, and suggest that when there are large differences, the stochastic model should be used. They note that the discrepancy is larger if the coefficient of imitation increases, either absolutely or relative to the coefficient of innovation.

Summary: Little incremental analytical insight is currently available due to taking a stochastic approach to modeling diffusion. Given the finding that diffusion patterns differ for deterministic and stochastic diffusion models, an empirical application can be expected to generate better forecasts of dynamic sales patterns if the nature of uncertainty is correctly modeled.

2.4. Diffusion as an aggregate of individual adoptions

A key assumption of the diffusion models discussed thus far is that the target market is homogeneous. In order to relax this assumption, two types of extensions of diffusion models have been proposed to allow for heterogeneous potential target markets. The first type is a heterogeneous potential adopter population or a heterogeneous target market. Although a general analytical solution cannot be obtained, the
Exhibit 2
Diffusion of innovation.

<table>
<thead>
<tr>
<th>Author/date</th>
<th>External or internal effects modeled</th>
<th>Deterministic or stochastic</th>
<th>Level of model</th>
<th>Variables found to influence diffusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fourn and Woodlock (1960)</td>
<td>External</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td></td>
</tr>
<tr>
<td>Mansfield (1961)</td>
<td>Internal</td>
<td>Both</td>
<td>Aggregate</td>
<td></td>
</tr>
<tr>
<td>Fisher and Fry (1971)</td>
<td>Internal</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td></td>
</tr>
<tr>
<td>Blackman (1974)</td>
<td>Internal</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td></td>
</tr>
<tr>
<td>Bass (1969)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td></td>
</tr>
<tr>
<td>Horsky and Simon (1983)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Advertising effects</td>
</tr>
<tr>
<td>Bass (1980)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Dynamic maximum</td>
</tr>
<tr>
<td>Horsky (1990)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Price, advertising, dynamic maximum, and income</td>
</tr>
<tr>
<td>Mahajan and Peterson (1978)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Dynamic maximum</td>
</tr>
<tr>
<td>Sharif and Ramanathan (1981)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Dynamic maximum</td>
</tr>
<tr>
<td>Kamakura and Balasubramaniam (1987)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Repeat purchases included</td>
</tr>
<tr>
<td>Mahajan, Wind and Sharma (1983)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Repeat purchases included</td>
</tr>
<tr>
<td>Olson and Choi (1985)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Repeat purchases included</td>
</tr>
<tr>
<td>Norton and Bass (1987)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Considers multiple generations of technology</td>
</tr>
<tr>
<td>Wilson and Norton (1989)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Considers incremental products based on one technology</td>
</tr>
<tr>
<td>Mahajan and Muller (1989)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Considers successive generations</td>
</tr>
<tr>
<td>Simon and Sebastian (1987)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Considers supply restrictions</td>
</tr>
<tr>
<td>Jain, Mahajan and Muller (1989)</td>
<td>Both</td>
<td>Deterministic</td>
<td>Aggregate</td>
<td>Considers supply restrictions, advertising, and distribution</td>
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<td>Tapiero (1983)</td>
<td>Both</td>
<td>Stochastic</td>
<td>Aggregate</td>
<td>Structurally stochastic</td>
</tr>
<tr>
<td>Boker (1987)</td>
<td>Both</td>
<td>Stochastic</td>
<td>Aggregate</td>
<td>Structurally stochastic</td>
</tr>
<tr>
<td>Eliashberg, Tapiero and Wind (1987)</td>
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<td>Stochastic</td>
<td>Aggregate</td>
<td>Stochastic parameters</td>
</tr>
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<td>Feder and O’Mara (1982)</td>
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<td>Stochastic</td>
<td>Aggregate</td>
<td>Incorporates firm’s Bayesian updating of probability of success</td>
</tr>
<tr>
<td>Jensen (1982)</td>
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<td>Stochastic</td>
<td>Aggregate</td>
<td>Incorporates firm’s Bayesian updating of probability of success</td>
</tr>
<tr>
<td>Reinganum (1981b)</td>
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<td>Stochastic</td>
<td>Aggregate</td>
<td>Incorporates game theoretical assumptions regarding firm behavior</td>
</tr>
<tr>
<td>Quirmbach (1986)</td>
<td>N/A</td>
<td>Stochastic</td>
<td>Aggregate</td>
<td>Incorporates game theoretical assumptions regarding firm behavior</td>
</tr>
<tr>
<td>Jeuland (1981a, b)</td>
<td>Both</td>
<td>Stochastic</td>
<td>Aggregate</td>
<td>Incorporates a Markov process describing consumer behavior</td>
</tr>
</tbody>
</table>
terns. If an individual consumer’s decision process is Bayesian, the aggregated diffusion pattern may be stochastic [Chatterjee and Eliashberg (1989); Lattin and Roberts (1989); Oren and Schwartz (1988); Roberts and Urban (1988)].

Alternatively, a heterogeneous potential market may be modeled by allowing optimal adoption timing for each individual. Diffusion patterns are obtained by aggregating the results of individual adoption timing decision models. In this case, if each individual makes an adoption decision based on the expected diffusion pattern of the resulting product, the two are interdependent and it may be possible to describe their behavior as a system of equations. We have not located any research in which this type of simultaneous solution is attempted.

Aggregation of optimal firm level adoption timing decisions has been carried out in several studies. Feder and O’Mara (1982) update the firm’s prior estimate regarding profitability of an innovation, predict firm adoptions, and aggregate them to obtain a sales diffusion pattern. The authors assume that potential customers are risk neutral and that the innovation dominates the previous technology. Under these conditions, they conclude that the shape of the diffusion pattern is critically dependent on the assumed distribution of potential customers’ initial beliefs. Jensen (1982) also develops a sales diffusion model assuming a given distribution of initial beliefs and a Bayesian learning process. Rather than update estimates of profitability, Jensen assumes that customers update the probability that an innovation will be profitable. Assuming that the innovation is profitable, the diffusion pattern depends critically on the variance of firms’ initial beliefs. Firm decisions may instead be modeled game theoretically. Reinganum (1981b) demonstrates in a two-firm game theoretic adoption model that a pure strategy Nash equilibrium requires one firm to adopt early and the other late. Quirmbach (1986) builds on Reinganum, obtaining a sales diffusion pattern for more than two firms by assuming that later adoptions result in decreasing incremental benefits as well as decreasing costs.

Summary: Individual consumer and firm adoption decisions described as Markov processes, Bayesian decisions, and game theoretical models have been aggregated to predict sales diffusion over time. However, the dependence of individual decisions on aggregate predictions implies a need to model the interaction between sales diffusion and optimal individual behavior.
2.5. Conclusions regarding sales diffusion models

Aggregate level diffusion models are useful in forecasting sales over time for a new technology. Sales forecasts are necessary to determine whether or not an innovative technology should be adopted, and if so, the optimal time at which to adopt. These predictions are also useful in planning production and in forecasting obsolescence of previous products.

Models for forecasting sales diffusion are being improved and extended in useful directions. Incorporation of such managerially relevant variables as product attributes, pricing, advertising, and distribution allows the model results to be applicable in a variety of decisions. Prediction of sales under such circumstances as changing potential market and restricted supply are important in actual decision situations. Not only are the theoretical results which have been obtained intuitively appealing, the majority of these models have been subjected to empirical testing for confirmation of fit to marketplace data. We see a key future development direction as being integration of the sales diffusion forecast into other models which make use of estimates of future sales or profits.

A summary of models described in this section is provided in Exhibit 2.

3. Conclusions and directions for future research

We review models for optimizing firms' decisions regarding adoption of a technological innovation in Part 1. The models discussed in this section predict expenditure patterns and timing of firms' adoption of innovation as a function of variables which are at best difficult to measure, such as rewards accruing to the first innovator, the expected cost and time required to obtain the knowledge needed to develop the innovation, the desirability of imitating the innovation should another firm develop it first, and the gap between the firm's current technology and the innovation. Although the resulting models provide analytical results which are consistent with intuition, empirical testing for confirmation is generally not performed. Future research in this area would benefit from use of more concrete predictors and application of the models to marketplace data.

In Part 2, we discuss models useful in forecasting aggregate sales for products based on a new technology. These sales diffusion models generally incorporate measurable or controllable variables such as size of the potential market, number of previous adopters, and components of the marketing mix. The development of aggregate level sales diffusion models has taken useful, practical directions, and the majority of these models have been verified using data from the marketplace. Further development of these models along the current lines will be valuable. Perhaps more importantly, the sales predictions from these models will be useful as inputs to other models.

Sales forecasts from diffusion models may be incorporated into models for firm adoption of innovation, as an indicator of expected profitability. Use of a diffusion curve to determine optimal timing of innovation is described by Kalish and Lilien (1986) and Yoon and Lilien (1986). Optimal timing of an incremental product based on the same technology as previous product(s) is discussed by Wilson and Norton (1989). Their analysis indicates that any incremental product should be introduced simultaneously with other product(s) based on the same technology, if it should be introduced at all. The authors call this the 'now or never' decision (p. 10). They test their results empirically using data for books which are printed in both hardcover and paperback. Timing the introduction of products based on successive generations of technologies may also make use of sales diffusion forecasts. Mahajan and Muller (1989) find that a new technology should be introduced either as soon as it is available, or else not until after the maturity stage of the previous generation. They call this the 'ASAP or at maturity' rule, which is a refinement of the 'now or never' rule of Wilson and Norton. Mahajan and Muller apply their model to introduction timing decisions for mainframe computers. Considerable further work is needed to better integrate sales diffusion models with firm innovation adoption models.

Sales forecasts impact firm decisions regarding adoption of a technological innovation which has not yet been adopted by other firms, as we have already discussed; these forecasts may also be useful in firm decisions to enter a market in which competing firms are already active. Al-
though the number of firms competing in an industry has been modeled previously [Gort and Klepper (1982); Gottinger (1987)], the attraction of a market depends on both the expected sales and the number of competitors. Therefore, we recommend development of models which capture the interaction of sales and number of firms in the marketplace.

It has been suggested that there is an optimal number of products per firm for a given technological innovation, and that this number is constant over time [Modis and Debecker (1988)]. We expect, however, that there is a more complex relationship between the optimal number of products and the optimal number of firms competing in the marketplace. One way to approach this question may be to model the relationship between sales and the number of products on the market. It may even be possible to simultaneously model sales, number of competing firms, and number of competing products. These are key directions for future research.

References


Lattin, J.M. and J.H. Roberts, 1989, “The role of individual level risk-adjusted utility in the diffusion of innovation”, Working paper (Graduate School of Business, Stanford University, Stanford, CA)


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