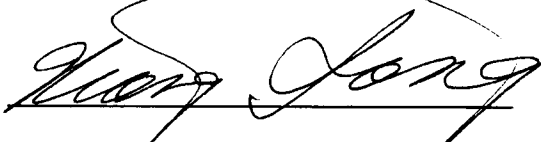
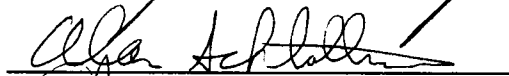
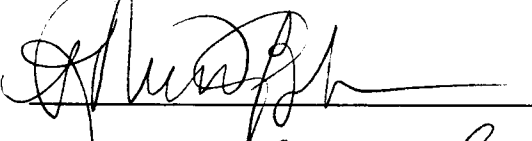


To the Graduate Council:

I am submitting herewith a dissertation written by Zheng-Ming Richard Sha entitled "Modeling the Market Growth of New Product — A New Model of Innovation Diffusion with Product Attribute Theory and a Descriptive Approach to the Behavior under Uncertainty." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy, with a major in Economics.


William E. Cole, Major Professor

We have read this dissertation
and recommend its acceptance


Accepted for the Council:


Associate Vice Chancellor
and Dean of the Graduate School

Modeling the Market Growth of New Products

— A New Innovation Diffusion Model with the Product Attribute Theory and
a Descriptive Approach to the Decision Behavior Under Uncertainty

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Zheng-Ming Richard Sha

August 1995

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Dedication

This Dissertation is dedicated to
my wife, Wendy
and my son, Brian

Acknowledgment

This study could not have been finished without help and support. My sincere thanks go to my dissertation chairman, Dr. William E. Cole, and the committee members, Dr. Robert A. Bohm, Dr. Hui X. Chang, Dr. Alan M. Schlottmann, and Dr. X Michael Song. Dr. Cole greatly encouraged me to undertake this research. He ensured the efficient operation of the committee. He also provided detailed comments on the late version of this dissertation. Dr. Bohm provided me with continuing support and encouragement throughout my graduate study at the University of Tennessee. He was there whenever I needed help. He reviewed the early draft of this dissertation and provided helpful comments. Dr. Chang and Dr. Schlottmann provided constructive and valuable comments that greatly enhanced the quality of this dissertation.

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Abstract

This study attempts to develop an alternative innovation diffusion model to comprehend the market growth behaviors of new products. It takes a microapproach and utilizes the product attribute theory to construct a multidimensional attribute space, in which the preference heterogeneity of consumers, their choice behaviors, and the consequent diffusion of a new product are analyzed. A descriptive approach to decision behavior under uncertainty is also adopted for the model development.

The model developed in this study, although similar to the Bass's benchmark model (1969), provides the advantage that the model parameters are composed of consumer behavioral and decision variables. The concept of diffusion frontier illustrates intuitively a dynamic process of new product diffusion. Studies on model properties show that the relative perceived advantages of a new product have a nonlinear relationship with its market potential. When such advantages are low, they affect only the diffusion rate of a new product, but not the market potential. When they are high, they affect the both. The salience of product attributes seems to be inversely related with the market potential of the product with no impact on the diffusion rate. Consumer behavioral parameters, as measured by the size and dynamic effects, have great impact on the patterns of new product diffusion. The results from our validation study support the proposed model specification: The generic square root term captures the long-term new

product market growth pattern; The inclusion of U^{new} term explains the variation around the general trend with the changes of consumer income and new product price.

It is concluded from this study that the product attribute theory can be used productively to develop an alternative model of new product diffusion. The inclusion of consumer perceptual, behavioral and decision variables into the model is theoretically more sensible, consistent and comprehensive. The model can offer rich managerial implications concerning new product forecasting and analysis.

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Chapter 1

Introduction

Innovation diffusion models provide an analytical or quantitative approach to the study of the diffusion of innovations. They can be used to study the diffusion, or the market growth, of a new product if we consider a new product as an innovation. The models used in such context are called new product diffusion models. New product diffusion models can serve as the primary analytical tools in linking product life cycles with certain strategic planning concepts (Mahajan and Wind 1986). The knowledge from such models is very much in demand. Firms, researchers, and policy makers have enormous interest in knowing more about the unique market growth patterns of new products as the pace quickens for new product development and introduction and the competition intensifies. Understanding the mechanisms and patterns of new product growth can help new product development and reduce the failure rates of new products.

The main objective of this study is to develop a micro approach model of new product diffusion that can serve as such a tool. In this introduction chapter, the author will identify major problems with previous innovation diffusion models and define both the objective and the approach to be taken in this study.

The Problem

Innovation diffusion models in marketing, management science, economics, and technological forecasting have attempted to model the time-dependent aspects of the innovation diffusion process. The best-known diffusion models in the areas above are those of Fourt and Woodlock (1960), Mansfield (1961), and Bass (1969). The Bass model can be regarded as an integration of the other two. It is the first well-known model to employ the innovation diffusion model to study the market growth of new consumer durable products. The above models follow the same underlying behavioral theory that an innovation is first adopted by a select few innovators who, in turn, influence others to adopt it, primarily through word-of-mouth communication. The modeling approach is aggregate because they do not deal with individuals' decision behaviors. Instead, they use the size of adoption population and the propensity to adopt for model development.

Since Bass published his benchmark model in *Management Science* (1969), a number of other models have been proposed to represent the diffusion process. Many were modifications and extensions of the Bass model. All these research efforts have constituted a rich stream of literature of innovation diffusion models. Mahajan, Muller, and Bass (1990) provided a very good review of this research stream with emphasis on the aggregate approach models. Critiques in the literature have identified the following major problems with the basic, as well as other extended, innovation diffusion models.

Market potential of the new product is constant over time. The Bass model assumes that the market potential m of a new product is predetermined. When cumulative

adoptions approach m , the market for the new product becomes saturated. However, many forces, both exogenous and endogenous, can influence the size of m . One example of the exogenous force is the size of a relevant population. Examples for the endogenous forces are price, advertising, product improvement, and other strategic variables. The extensions that included price variable into the Bass model were made by several researchers (e.g., Mahajan and Peterson 1978; Jeuland 1981), but the controversy arises in terms of how to incorporate it. It is not clear whether the price should affect the market potential or the current diffusion rate.

Diffusion of an innovation is not influenced by marketing strategies. Strategic variables such as price and advertising were not considered in the Bass model. Because the inclusion of such variables into the basic diffusion model can furnish the model with potential implications for managerial purposes, researchers have devoted enormous efforts to modifying and extending the Bass model. However, the specification of price and advertising variables in such extended models remains a controversial issue (e.g., Robinson and Lakhani 1975; Mahajan and Peterson 1978; Horsky and Simon 1983; Simon and Sebastian 1987). No theoretical support was given to any such extensions, and the empirical supports were inconclusive (see Mahajan, Muller, and Bass 1990, p. 20).

The nature of an innovation does not change over time. Continuous technological progress and market competition accelerate the pace of new product improvement and development, especially in high-tech industries. They are expected to affect the patterns of new product growth. The only extension by Norton and Bass (1987) assumed

exogenous changes of the market potential for the new product generations. More inquiries remain to be done.

Other problems with the models are that the diffusion of an innovation is independent of all other innovations; that the diffusion process is binary; that product and market characteristics do not influence the diffusion patterns; that there are no supply restrictions; and that there is only one adoption by adopting unit. Although these problems have been tackled by many researchers, Mahajan and Muller (1979) commented that the consideration of decision variables into the Bass model had been "piece meal" (Mahajan and Muller 1979). The inclusion of such variables has been made in a rather *ad hoc* way (Kalish 1985). Most "extensions and refinement of the Bass model add something to the paradigm but none overrides its basic character" (Norton and Bass 1987).

Careful examination of the problems associated with the Bass model and its modifications and extensions leads to such a conclusion: The aggregate approach models may be ill-positioned by their focus on the communication aspect rather than on the decision aspect of an innovation diffusion process. Such an emphasis on communication can be stated as: "The diffusion of an innovation is a process by which that innovation is communicated through certain channels over time among the members of a social system" (Rogers 1983, p. 5; Mahajan, Muller, and Bass 1990, p. 1). Because these models have their roots and analogies in the models of epidemics in biology and ecology (Bailey 1957; Pearl 1925; Peilou 1969) they bear the same character as those models.

Thus, for the models of innovation diffusion to be methodologically correct, an innovation must be so strong that everyone will adopt it if he/she is aware of it. The reality, however, is not so simple. An individual who receives the information about an innovation needs time to digest and make his/her decision. If there are differences in individuals' adoption behaviors, the innovation diffusion models that implicitly treat people as homogeneous may fail to describe the actual diffusion patterns.

The limited ability of aggregate approach models to consider decision variables calls the development of models from an alternative approach, i.e., the micro-level approach. Since the diffusion of an innovation is practically the aggregated result of individuals' adoption behaviors, micro approach models that begin with the consideration of on individual's behavior can be flexible and powerful to account for the impact of such decision variables. The impact of such variables on an individual's decision behavior has a more sensible theoretical and empirical guidance.

To be sure, the models that deal with individuals' adoption behaviors toward an innovation have been around for some time (see Gatignon and Robertson 1986). However, the focus of such innovation adoption models is not on the aggregate market response, but on the evolution of the stages that an individual goes through to adopt an innovation. In theory, we can convert adoption models into diffusion models if we can integrate individuals' adoption behaviors into the aggregated market responses. In practice, however, such conversion can be complicated. Analytical relationships need to be specified, and consumer distributions should be considered if we are to build a

diffusion model from individuals' adoption behaviors. Efforts in this direction started in the early 1980s, but the models are still "at a preliminary stage" (see Mahajan and Wind 1986, p. 153).

The Objective and the Approach

The primary objective of this study is to develop and validate a micro approach model of new product diffusion. The micro approach means that the model takes a "build-up" perspective. The diffusion of a new product is considered the aggregated result of individual consumers' adoption behaviors. This approach has the advantage of incorporating various decision variables into the model because their impact on individuals' decision behaviors can be examined with theoretical guidance. The model to be developed in this study is expected to provide an analytical framework for the study of the dynamic market growth behaviors of new products.

To accomplish this goal, this study draws upon the latest research findings and thoughts from economics, marketing and management sciences, and psychology. In particular, it adopts product attribute theory from economics and marketing and the descriptive approach to the decision behavior under uncertainty from psychology. The model to be developed reflects this theme: The diffusion of a new product is primarily the result of the reduction of uncertainty in a heterogeneous population.

Heterogeneity in consumers' preference will be studied in the framework of product attribute theory. A set of relevant product attributes will be used to define a

multi-dimensional space in which consumer heterogeneity, consumer choice behavior, and the nature of a new product are analyzed.

The product attribute theory emerged from psychology (Luce and Tukey 1964) and economics (Lancaster 1966, 1971; Rosen 1974) and received extensive applications in marketing and management (e.g., Green and Srinivasan 1978; Shocker and Srinivasan 1974). The core of this theory is that a consumer demands a new product not for the sake of the product itself, but for the benefits conveyed by the product. Although this area of research contains a rich body of literature, there has been little effort to integrate it with the study of innovation diffusion models.

The impact of uncertainty reduction will be attempted with a descriptive approach. Different from the normative approach, the descriptive approach is concerned with how an individual *does*, rather than *should*, behave under uncertainty (see Bell, Raiffa, and Tversky 1988). Such an approach is more appropriate for the study of new product diffusion where uncertainties are pervasive and consumer judgment biases persist. This approach also enables the development of a parsimonious model.

Since diffusion of a new product is an aggregated outcome of individual consumers' adoption behaviors, particular attention will be paid to the mechanism of the aggregation. Consumer distributions in a relevant attribute space will be considered and the forces that cause the dynamics of new product diffusion will be examined.

An empirical study will be conducted for the purpose of validation after the model is developed. The empirical study will apply a flexible transformation, the Box-Cox

transformation, to the model variables to identify its optimal functional form. The model performance will be evaluated in comparison with that of an equivalent of the Bass model.

Before concluding the thesis, this study will examine the implication of the proposed model with regard to the improvement of the process of new product development and to the reduction of new product failure rates.

Chapter 2

Relevant Literature

This chapter is a review of three separate but interrelated bodies of literature: the diffusion of innovations, models of innovation diffusion, and decision behavior under uncertainty. A brief review of the studies on diffusion of innovations highlights its major components and provides a broad background for this study. Innovation diffusion models take an analytical or quantitative approach to the study of diffusion of innovations. The review of these models attempts to examine the relative merits of their modeling approaches. The purpose of a brief review of recent progress in individuals' decision making under uncertainty is to provide insights to and guide the development of a micro approach model in this study.

Innovations Diffusion Study in Brief

The study of the diffusion of innovations has a long history, resulting in a body of literature consisting of several thousand articles, books, and assorted publications. The diffusion process is perhaps one of the most widely studied social phenomena and is reportedly found in nearly two dozen distinctive academic disciplines (Mahajan 1985). The disciplines involved in this study are geography, sociology, marketing, economics,

education, and so forth. Because a complete review of this topic is not the purpose of this study (a complete review is provided by Rogers 1983), I will only highlight the major components of the innovation diffusion theory to provide a background for this dissertation.

What Is the Diffusion of Innovations?

What is an innovation? According to Rogers (1983, p. 11),

an innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption. It matters little, so far as human behavior is concerned, whether or not an idea is "objectively" new as measured by the lapse of time since its first time use or discovery. The perceived newness of the idea for the individual determines his or her reaction to it. If the idea seems new to the individual, it is an innovation.

The above definition emphasizes newness as the primary characteristic of an innovation. The latitude of the newness so defined can be very wide. An innovation can be a novel high-tech product, which provides both material and perceptual newness, or a clothing fashion, which provides probably only perceptual newness. The above definition is used widely in fields such as sociology, marketing, and communications. The economics tradition seems to put more substantial value on an innovation. Economists distinguish an innovation from an invention. "An invention, when applied for the first time, is called innovation" (Mansfield 1968, p. 99).

What is diffusion? Diffusion, according to Webster,¹ is an action of being spread out in every direction. Diffusion is a dynamic process. The study on diffusion deals explicitly with time, especially a physical movement over time. Diffusion is studied in both natural and social sciences, e.g., the diffusion of heat in solid or liquid materials in physics, the diffusion of news and rumors among people in communications, and the diffusion of epidemics in a population in public health.

What is the diffusion of innovations then? The diffusion of innovations is widely studied in social sciences. According to Rogers (1983, p. 5), the diffusion of an innovation is

a process by which an innovation is communicated through certain channels over time among the members of a social system. It is a special type of communication, in which the messages are concerned with new ideas.

As such, the diffusion process consists of four key elements: innovation, communication channels, time, and the social system. As a theory of communications, diffusion theory's main focus is on the means by which an innovation is transmitted to or within a social system.

The economics tradition views the diffusion of an innovation simply as the spread of the innovation. Without getting into details, Mansfield described innovation diffusion as a "learning process" that takes place "among a considerable number of users and producers, rather than being confined to a research laboratory or a few firms" (1968 p.

¹ Webster International Dictionary, 3rd edition, 1971.

112). Recently, economists have attempted to include such learning, as well as firms' optimal decision processes, into their models of innovation diffusion (e.g., Tsur, Sternberg, and Hochman 1990).

The Scope of the Study

The scope of innovation diffusion study is extensive. The issues it inquires into range from the innovation itself to its social consequences. The typical issues include: Why and how an innovation is generated? Which types of persons or units are more responsible for it? How the innovation decision is made? What attributes affect the diffusion? Which types of persons or units are innovators, or other adoption categories? What is the impact of opinion leaders and networks? What is the social consequences or impact due to the diffusion of an innovation?

Field study or case study is the typical method of study for the diffusion of innovations. The research methodology has been significantly influenced by that of Iowa hybrid corn since Ryan and Gross published their research in 1943. Employing a structured questionnaire and one-shot survey interviews, Ryan and Gross set forth a template for such study. The attention of the study was on the variables related to innovativeness, the factors explaining the rate of diffusion, and the roles of communication channels at different stages of the innovation decision process. However, the overwhelming influence of their study was not completely beneficial. "An overly close copying of the classical diffusion paradigm by later researchers, who were often

investigating diffusion of a quite different type, led to inappropriate methodologies and mistaken theoretical thrust" (Rogers 1983, p. 56). Despite thousands of publications accumulated on this subject, Rogers commented that the study has been "miles long but inches deep" (Rogers 1983).

With its primary interest in technological changes, the economics tradition is mostly concerned with the impact of such changes on and its interaction with economic growth, the role of government, and corporate R&D. It is also interested in the consequences of technological changes for industrial automation, labor displacement, economic adjustment, and relevant policies.

The studies of innovation diffusion evolve as a theory of innovation diffusion. The theory conceptualizes a five-stage innovation decision process and five attributes for the diffusion of an innovation, as summarized in the following paragraphs².

The Innovation Decision Process

Rogers theorizes that the innovation decision process involves the following five stages: knowledge, persuasion, decision, implementation, and confirmation. At the knowledge stage, an individual is exposed to an innovation and thus becomes aware of it. The persuasion stage follows, in which the individual forms a favorable or unfavorable attitude toward the innovation. The individual makes the decision to adopt or reject the innovation in the decision stage. Then comes the stage of implementation if indeed the

² The following is largely based on Rogers' description in his book, *The Diffusion of Innovations* (1983).

individual adopts the innovation and puts it into use. Confirmation is the fifth, but not final, stage in the innovation decision process because the individual is likely to seek reinforcement for the innovation decision he/she has already made. Such a five-stage decision process is dynamic. As a result, individuals may exhibit four different adoption behaviors: adoption and continued adoption, adoption and discontinuance, rejection and then later adoption, and rejection and continued rejection.

Attributes for the Diffusion of Innovations

Five attributes influence the diffusion rate of an innovation. They are categorized as the relative advantages, compatibility, complexity, trialability and observability of an innovation.

Relative advantages is the degree to which an innovation is perceived as being better than the idea or item it supersedes. They can be the gains in economic profitability, social status, or the like. The more the relative advantages, the quicker an innovation will diffuse. The nature of an innovation largely determines its relative advantages for potential adopters.

Compatibility is the degree to which an innovation is perceived as consistent with the existing values, past experience, and needs of potential adopters. An innovation that is not compatible with the values of potential adopters is less likely to be accepted. The compatibility issue can arise under many circumstances, e.g., when we want to add a new software or hardware to current computer systems.

Complexity is the degree to which an innovation is perceived as relatively difficult to understand and use. Although empirical evidence is far from conclusive, a plausible proposition is that the complexity of an innovation, as perceived by members of a social system, is negatively related to the rate of the adoption.

Trialability is the degree to which an innovation may be experimented with on a limited basis. An innovation that is trialable is less uncertain for the adopters. It is believed to be positively related with the diffusion rate.

Observability is the degree to which the results of an innovation are visible to others. It is also believed to be positively related with the diffusion rate.

Empirical studies were conducted regarding the effects of these five attributes for the diffusion of an innovation. Using a meta analysis method, Tornatzky and Klein (1982) analyzed 75 previous studies that empirically investigated the relationship between these attributes and the rate of innovation diffusion. Of five attributes, three were found to be most significantly related to the diffusion of innovations. These three attributes were relative advantages, compatibility and complexity. The significance of the other two was inconclusive.

Innovations Diffusion Models

This review covers exclusively analytical models, which can be roughly classified as being either aggregate or micro approach. The aggregate models are built directly with aggregate level variables. In contrast, the micro approach models begin with the

consideration of individual decision behaviors. Innovation diffusion models are expected to provide analytical descriptions for the diffusion of innovations at the market level. The following review is divided by the approach.

Aggregate Approach Models

The Bass Model

The Bass (1969) model is a well-known benchmark innovation diffusion model that is used to explain the market growth of new products. Though it is virtually a contagion model, the clever interpretation of innovators and imitators by Bass makes the model relevant for management purposes. Subsuming the models proposed by Fourt and Woodlock (1960) and Mansfield (1961), Bass (1969) assumed that the potential adopters were consisted of two groups. Of these two groups, one group was influenced only by mass-media communication (external influence) and the other only by word-of-mouth communication (internal influence). He termed the first group “innovators” and the second group “imitators.”

Let $f(t)$ be the probability to adopt an innovation in a relevant population, $F(t)$ the cumulative fraction of adopters at time t , p the coefficient of innovation, and q the coefficient of imitation. The formulation of the Bass model can be expressed as

$$f(t)/[1 - F(t)] = p + qF(t). \quad (2.1)$$

Let m be the size of a relevant population, which can be interpreted as the market potential for an innovation or a new product, given that each individual adopts only one unit, $n(t)$ be the rate of adoption or the sales at time t , and $N(t)$ be the cumulative volume of adopters. Obviously, the relationship $mf(t)=n(t)$, $mF(t)=N(t)$ holds according to the definitions. Thus, (2.1) can be expressed in another form,

$$n(t) = \frac{dN(t)}{dt} = p[m - N(t)] + \frac{q}{m} N(t)[m - N(t)]. \quad (2.2)$$

Both Equations (2.1) and (2.2) can yield the well-known S-shaped cumulative diffusion curves.

Figure 2.1 shows the analytical structure of the Bass model. The peak of the rate of adoptions, or the maximum sales of a new product, occurs at time T^* , a point commonly referred as the inflection point. Once initiated, the diffusion pattern is symmetric with respect to time around the peak time T^* up to $2T^*$. The Bass model implies that the innovators are responsible for the occurrence of the diffusion process although both innovators and imitators contribute to its progress. The initial adoption or sales is determined by the product of p and m . Innovators exist throughout the whole diffusion process but their influence, however, diminishes due to the growing number of imitators over time.

Though highly parsimonious, the Bass model provided a good fit to the patterns of market growth for various consumer durable products (see Bass 1969). Of eleven

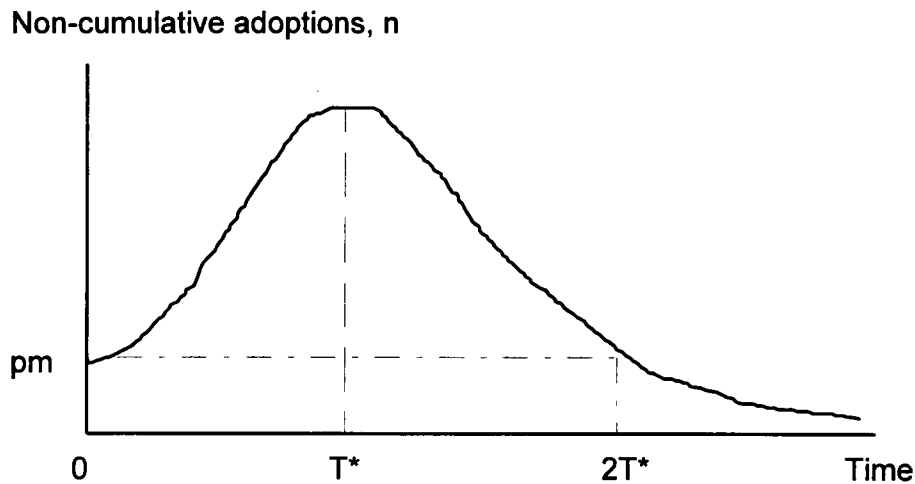


Figure 2.1 Analytical Structure of the Bass (1969) Model

consumer durable products in his study, five fitted the model with R-square greater than 0.9, four greater than 0.8, one around 0.74, and the worst around 0.57. All parameter estimates yield consistent signs, and most are statistically significant. The result is so encouraging that it sparks a whole new stream of research thereafter.

Shortcomings of the Bass model include the failure to consider decision variables and the inflexibility to describe nonsymmetric diffusion patterns. Its managerial applicability is thus limited. The past two decades have seen substantial improvements at overcoming these shortcomings. The next two sections discuss these improvements.

The Bass Model Extensions 1: Decision Variables

Decision variables are those that can be controlled or implemented for strategic purposes, e.g., the price, features, and functions of new products and the advertising for the products. Business scholars and practitioners are always interested in the impact of these variables on the diffusion of new products.

Price is the most important decision variable because it is the most easily observed by consumers and it can be quickly controlled by firms. It affects consumers' preference for the new products and the consequent market demand. The price effect has been interpreted in two different ways for the extension of the Bass model. First, price can affect the current market demand, or second, it can influence the total market potential of a new product. Robinson and Lakhani (1975) first suggested that the price of a new product affected its current demand, or the rate of diffusion by the terminology in the study of innovation diffusion. Assuming $G(P)$, the impact of price on the diffusion rate, they formulated a model as below:

$$\frac{dN(t)}{dt} = (m - N(t)) \cdot (a + b \cdot N(t)) \cdot G(P). \quad (2.3)$$

Note that the first two terms are identical to the Bass model, granted $a=p$ and $b=q/m$. Robinson and Lakhani argued that marketing efforts such as pricing affected the diffusion process in a multiplicative way. However, they did not provide empirical support to such model specification. Their focus was normative, i.e., how to price a new product over its

life cycle given the existence of diffusion phenomenon. Their model was further studied by Dolan and Jeuland (1981) and Jeuland and Dolan (1982), whose approaches were normative as well.

The model formulation (2.3) assumes that the market potential remains the same no matter how the price of a new product changes. Mahajan and Peterson (1978) argued that the market potential is dynamic, varying over time as a result of a firm's marketing efforts and exogenous factors such as the increase of population size, economic conditions, and the like. Though such modeling perspective is subsequently investigated by Feichtinger (1982) and Jorgenson (1983), the literature credits this model specification to Mahajan and Peterson (1978) for their initial idea. Their model can be expressed as

$$\frac{dN(t)}{dt} = (m(P) - N(t)) \cdot (a + b \cdot N(t)). \quad (2.4)$$

The $m(P)$ in the above equation is the dynamic market potential for a new product as a function of its price.

Observing that the prices of new products generally decrease throughout the diffusion process due to decreased manufacturing costs that result from the well-known learning effect, Bass (1980) proposed a multiplicative model to extend his original model. He assumed that current market demand was affected by price with constant elasticity, $G(P) = e^{-dP}$. Such effect worked in addition to an exogenous product life cycle described by his bench-mark model, i.e., $dH(t)/dt$. Therefore, he obtained

$$\frac{dN(t)}{dt} = \frac{dH(t)}{dt} \cdot G(P). \quad (2.5)$$

This model specification is the same as that by Robinson and Lakhani (1975) except for an explicit consideration of the function $G(P)$.

Advertising is another important decision variable, especially in the marketing arena. The purpose of advertising is to provide and assimilate information but sometimes advertising may exert undesirable persuasion. Advertising is typically modeled as to promote consumer awareness. Horsky and Simon (1983) extended the Bass model by treating its coefficient of innovation as a function of advertising expenditures on new products. The functional relationship was logarithmic in the light of diminishing returns of advertising expenditures. Simon and Sebastian (1987), on the other hand, suggested that advertising was more likely to influence the coefficient of imitation in the intermediate life cycle stages of a new product because the objective of the advertising content then was to influence potential adopters through social pressure. Both studies found empirical supports for their own models.

7 Kalish (1985) suggested a more comprehensive model that considered the effect of uncertainty and information spread and the consumer distribution as a function of their reservation prices. Kalish assumed that there were uncertainties about the performance of new products from the consumers' perspective. Because of such uncertainties, risk-averse consumers would discount their valuation of the products. The uncertainties were

gradually reduced as more information about the product became available. Let U be the discount factor due to uncertainty and $I(t)$ the number of the informed individuals. At any time t , the size of potential population was determined by the number of people who were aware of the product and whose discounted reservation prices were above the market price, i.e., $m(P/U) \cdot I$. He further assumed that the adoption did not take place immediately and that actual adoptions at time t were only a fraction of the potential adoptions. The fraction was represented by k , a parameter less than one. The value of k would be high if a buying process were simple and low if the buying process were complicated. The two-stage model suggested by Kalish states the following:

$$\frac{dN(t)}{dt} = \left[m \left(\frac{P}{U(N(t) / N_0)} \right) \cdot I - N(t) \right] \cdot k \quad (2.6)$$

and

$$\frac{dI(t)}{dt} = [1 - I] \cdot \left[f(A) + bI + b' \left(\frac{N}{N_0} \right) \right] \quad (2.7)$$

where the discount factor U is assumed to be a function of the saturation level of a market. $f(A)$ in (2.7) is a function for advertising effectiveness.

More recently, Bass and Krishnan (1992) extended the Bass bench-mark model by incorporating decision variables in another way. They adopted the multiplicative form but utilized a mapping function to infer the impact of price and advertising on the diffusion of new products.

The attempt to explain new product diffusion process as the result of consumer heterogeneity has been made in the aggregate approach models. Russell (1980) commented that the Bass (1980) model could be explained in an alternative way. The diffusion of new products was caused by their falling prices over time, which made the products affordable for more consumers. This idea was evaluated empirically by Horsky (1990), who considered both income-price and word-of-mouth processes. He found a strong income-price effect and weak or even no word-of-mouth effect in all product classes studied.

Product attributes affect the diffusion of new products. Several authors have attempted to incorporate product attributes into the Bass model. Srivastava et al. (1985) considered the coefficient of innovation as a function of fourteen attributes of investment alternatives. They found that two of these fourteen attributes affected the diffusion process significantly. Weerahandi and Dalal (1992) modified the Bass model in a different way. They took a two-stage modeling approach. The purchase occasions at the first stage followed a conventional diffusion process. A binary choice model was adopted in the second stage to include product attributes into their model to investigate the market penetration of fax machines.

The Bass Model Extensions 2: Flexible Diffusion Patterns

The Bass model (1969) is virtually a communication model that involves several assumptions to simplify the communication processes. The constancy of p and q assumes

that the importance of coefficients of internal and external influences does not change over time. This assumption is tenuous because the internal influence of word-of-mouth is likely to increase, decrease, or remain constant over time (Hernes 1976). Easingwood, Mahajan and Muller (1983) suggested that the time-varying nature of the word-of-mouth effect be included into the Bass model. They specified that the coefficient of internal influence varied systematically over time as a function of the penetration level, i.e.,

$$w(t) = q \left[\frac{N(t)}{m} \right]^\alpha, \quad (2.8)$$

where α is a constant, $w(t)$ the time-varying coefficient of internal influence from their model, and $N(t)/m$ the level of penetration. By substituting (2.8) into the Bass model (2.1), they obtained a so-called nonuniform-influence (NUI) model,

$$\frac{dF(t)}{dt} = [p + qF^\delta(t)] \cdot [1 - F(t)]. \quad (2.9)$$

Much research effort has been directed at modifying the communication mechanisms of the Bass model. The models developed following this direction are called flexible diffusion models. They helped to explain the nonsymmetric diffusion patterns observed in the real world. The specifications of several representative models are listed in Table 2.1 (based on Mahajan, Muller, and Bass 1990).

Table 2.1 Specifications of Flexible Diffusion Models

Model Developer	Model Specification	Targeted Problems
1. Bass (1969)	$\frac{dF}{dt} = (p + qF)(1 - F)$	Consumer durables retail service, Educational, industrial process, etc.
2. Gompertz Curve (see Hendry 1972; Dixon 1980)	$\frac{dF}{dt} = qF \ln\left(\frac{1}{F}\right)$	Consumer durable, agriculture.
3. Mansfield (1961)	$\frac{dF}{dt} = qF(1 - F)$	Industrial, technology, administrative, etc.
4. Floyd (1962)	$\frac{dF}{dt} = qF(1 - F)^2$	Industrial.
5. Jeuland (1981)	$\frac{dF}{dt} = (p + qF)(1 - F)^{1+\gamma}$	Consumer durable.
6. Nonuniform Influence (Easingwood, Mahajan, and Muller 1983)	$\frac{dF}{dt} = (p + qF^\delta)(1 - F)$	Consumer durable, educational.
7. Nonsymmetric	$\frac{dF}{dt} = qF^\delta(1 - F)$	Medical innovations.
8. Nelder (1962) McGowan (1986)	$\frac{dF}{dt} = qF(1 - F^\phi)$	Agriculture.
9. Von Bertalanffy (1957) Richards (1959)	$\frac{dF}{dt} = \frac{q}{1-\theta} F^\theta (1 - F^{1-\theta})$	Agriculture.
10. Flexible Logistic Growth (Bewley and Fiebig 1988)	$\frac{dF}{dt} = q[(1 + kt)^{1/k}]^{\mu-k}$	Telecommunication.

Other Modeling Approaches

Two alternative and distinctive modeling approaches can be classified as aggregate approaches. These two models are the threshold model of collective behavior and an information theoretical approach model.

The threshold model of collective behavior can be used to explain the diffusion of innovations. According to Granovetter and Soong (1983; 1986), the model overcomes two critical assumptions underlying the Bass model: homogeneous mixing in a population and identical individuals. The homogeneous mixing means that every member in a relevant population exhibits the same behavioral nature, as implied in the Bass model. Identical individuals mean that each individual has the same likelihood to adopt an innovation. Observing widespread heterogeneity in any population, Granovetter and Soong built their models upon the notion of individuals' thresholds. An individual's threshold for action was a function of his/her own value and the number of participants or adopters in a relevant population. The collective behaviors in a population could be derived from there. The model was able to explain some interesting phenomena of collective behavior for the diffusion of innovations. By focusing on primary effects, this modeling approach avoided the issue of stochasticity, an advantage according to the authors.

The modeling approach of the threshold model sounds like a micro approach, but its analytical methodology is closer to that of the aggregate approach. It is important to note that the boundary between aggregate and micro approaches is not clear-cut.

Sometimes the boundary may become blurred when population heterogeneity is examined in detail.

The information theoretical model of innovation diffusion (Semple and Wasilinko 1976) begs the principle of entropy maximization. Diffusion was considered a process of the change in a system's entropy value. When the diffusion process was completed, the entropy of a social system reached its maximum. This approach had very weak decision or managerial relevance. Recent researches did not report any further progress following this direction.

Micro Approach Models

Micro approach models consider the diffusion of innovations as the result of individuals' adoption behaviors. This approach views the diffusion of an innovation basically as a process of uncertainty reduction in a heterogeneous population. Three elements are therefore essential for the development of a micro approach model: (1) The specification of heterogeneity in a population, (2) the mechanism of uncertainty reduction with regard to an individual's decision behavior, and (3) the aggregation of individuals' behaviors.

Heterogeneity in a Population

Heterogeneity exists almost everywhere in a population. Individual consumers in a population differ in their incomes, preferences, risk attitudes, capabilities of risk-bearing, initial perceptions about an innovation, reservation prices, etc.

To model the diffusion of a new technology, Jensen (1982) considered that individual firms were heterogeneous in their reservation probability p^* , or the probabilistic belief that the new technology would be profitable. Such differences were the result of firms' managerial expertise and previous experiences with other innovations. Under the assumption that individuals are sufficiently risk-averse, Oren and Schwartz (1988) considered a collapsed scale measure, indifference threshold ρ , that accounted for the effects of previous success, productivity, profitability, and price. Individuals were distributed along this scale following an exponential pattern described by $F(\rho) = 1 - \exp(-\gamma \rho)$. More recently, Chatterjee and Eliashberg (1990) characterized the behavior of an individual as a function of his/her initial perception, preference characteristics, and the responsiveness to information. Two composite measures, α and β , were used to characterize the differences among individuals. Individuals are classified into three groups according to the combination of these two measures. Despite all these efforts, the measurement and implementation of the population heterogeneity have always been the common weakness in previous studies. No attempt was made to specify the heterogeneity based on consumer preference differences, although preference is a

primary source of consumer heterogeneity, and significant support is found in the literature.

Some researchers did not use population heterogeneity as a contributing factor to derive the diffusion curves because their focus was instead on intrafirm technological diffusion (e.g., Stoneman 1981; Tsur, Sternberg and Hochman 1990). Therefore, optimal decision rules were used for the development of those models. Those models, however, should be categorized more precisely as the models of technological substitution.

Reduction of Uncertainty and an Individual's Decision Behavior

Uncertainty obscures the benefits of an innovation. Information seeking and learning can reduce the uncertainty associated with the innovation. In previous studies, a stream of information such as the performance of an innovation, is generated in the process of innovation diffusion. An individual garners this information in the Bayesian fashion.

The performance of an innovation is assumed to have a true level μ and variance σ^2 . Information is conveyed by a discrete series $z_1, z_2, z_3, \dots$. An individual observes it with mean m , his/her expected performance of an innovation, and variance s^2 , the degree of his/her perceptual uncertainty regarding the innovation. An individual updates his perception about the innovation according to the following Bayes's rule:

$$m_i = \frac{m_{i-1} / s_{i-1}^2 + z_i / \sigma^2}{1 / s_{i-1}^2 + 1 / \sigma^2}, \quad (2.10)$$

$$s_i^2 = \frac{1}{1 / s_{i-1}^2 + 1 / \sigma^2}. \quad (2.11)$$

This technique was used by Chatterjee and Eliashberg (1990), Tsur, Sternberg and Hochman (1990), and Oren and Schwartz (1988).

Jensen (1982) applied the Bayes's principle in a slightly different way. In his study of interfirm diffusion of technology, he postulated that a firm perceived an innovation as profitable with some probability θ_1 and unprofitable with other probability θ_2 , and that

$0 < \theta_2 < \theta_1 < 1$. If p was the firm's current probabilistic belief that $\theta = \theta_1$, then it estimated θ by $q(p) = p\theta_1 + (1-p)\theta_2$. A firm assigned a subjective probability g to the event $\theta = \theta_1$. The pattern of incoming information followed the Bernoulli trial. If k pieces of information were favorable out of n observations, a firm updated its belief that $\theta = \theta_1$ by,

$$p(n, k, g) = \left[1 + \left(\frac{\theta_2}{\theta_1} \right)^k \left(\frac{1 - \theta_2}{1 - \theta_1} \right)^{n-k} \left(\frac{1 - g}{g} \right) \right]^{-1}. \quad (2.12)$$

An individual's decision behavior was modeled most of the time with the utility instrument and sometimes with optimality techniques (e.g., Jensen 1982). Adopting the

von Neumann-Morgenstern (1947) framework and utility function suggested by Keeney and Raiffa (1976), Chatterjee and Eliashberg (1990) proposed a two-attribute utility function

$$U(\tilde{x}_i, p) = k_x u_x(\tilde{x}_i) + k_p u_p(p), \quad (2.13)$$

where $\tilde{x}_i$ was the potential adopter's uncertain perception of the performance of a new product after receiving i units of information and p the price of the new product. The expected utility was adversely affected by the variability of perceived performance. With the assumption that $u_p(p) = -p$, an individual's decision criterion could be stated as $E(u_x(\tilde{x}_i)) \geq kp$. After some mathematical operations, an individual's decision behavior could be obtained as a composite variable y_i . Assuming that information was generated at a constant rate, they formulated that the changes of y_i followed a Weiner process. The probability of adoption by the individual at time t thus could be obtained as a function of the information he/she received. They derived several commonly observed diffusion curves by aggregating over all possible values of α and β . The utility instrument was used by other researchers as well (e.g., Oren and Schwartz 1988).

Optimality technique was used for modeling an individuals' decision behavior. Jensen (1982) considered two levels of returns R_i , R_o (R_i is a stream of returns a firm can get if it adopts an innovation, and R_o is a stream of returns a firm gets if it does not adopt the innovation) and a parameter θ (the probability of R_i being realized) in his model. A

firm used the expected return $R = \theta_1 R_1 + (1 - \theta_1) R_0$ as a criterion for its decision making. As the firm learned according to the Bayes's rule and updated the perceived probability θ , it revises its perception about the expected return from the innovation. A firm finally decides to adopt an innovation if the expected return, less the fixed cost, exceeds the return without the adoption. Tsur, Sternberg, and Hochman (1990) used a similar technique for their model development.

The methodology to model the learning and decision behavior was almost exclusively the Bayesian method and optimality techniques from previous studies. Although well-founded on the principles of statistics, such a normative approach has some shortcomings. One shortcoming is the potential difficulties in implementation and the other, more critical weakness is the challenge to the validity of the normative approach for the modeling of individuals' decision behaviors in the instance of innovation diffusion. This issue will be discussed in the next section.

Aggregation

Aggregation is an essential step to obtain at the market level the expression for the diffusion of innovations from individuals' decision behaviors. Aggregation is typically performed on the scales along which individuals are distributed. To obtain the aggregate diffusion patterns, Jensen (1982) considered that the original beliefs of firms in an industry were distributed on $[0,1]$ according to some cumulative function $F(p)$. Oren and Schwartz (1988) considered a cumulative distribution along the scale of a risk-aversion

parameter ρ . They specified the rate of adoption as $\dot{N}(t) = \lambda F(\dot{\rho})$, where the dot on the top of a variable indicates the changes of that variable. They also added a birthrate effect to the adoption rate.

One weakness of these models is the lack of clear specification of the force(s) that moves the “threshold” along the scale over time. In other words, they have not designated an internal mechanism on how adoption behaviors in one period affect the adoption behaviors in later periods. It is not enough to assume some cumulative distributions along relevant scales and to treat the diffusion rate simply as the change of the cumulative distribution in certain periods. By doing so, one misses an important factor that controls the speed of diffusion.

Individual's Decision Behavior Under Uncertainty

The review of micro approach models indicates that the ways to specify uncertainty reduction and an individual's decision behavior are critical to the development of an appropriate model. The specification affects not only the implementation, but also the validity of the model.

Recent advances on the subject of decision making under uncertainty bring up some insightful thoughts. The research findings challenge the validity of the normative approach to the decision making under uncertainty. The review in this section provides the rationale for attempting a descriptive approach in this study.

The Violation of the Normative Approach

Long ago, mathematicians and economists developed a normative approach to study individuals' decision behaviors. Central to the normative approach is the well but maybe narrowly defined concepts of rationality and optimality. Based on a simple set of logic, the normative approach illustrates how a rational individual *should* behave. It differs from the descriptive approach, which concerns how an individual *does* make decisions (whether or not rational). The descriptive approach is typically employed by psychologists and behavioral scientists. Although the normative approach is still a widely adopted analytical tool, accumulated evidence has shown that mere logic is not enough to explain the complicated behavior exhibited by individuals facing uncertainty and that the basic premises underlying the normative approach are often violated. These findings are beginning to influence economic studies in the areas of benefit-cost/risk analysis and public policy, for example (Kask and Maani 1992).

A well-known violation of the normative approach is preference reversal. The economics tradition treats it as an exception and puts little effort into exploring its underlying mechanisms. Lichtenstein and Slovic (1971) conducted a careful investigation of this issue. When the subjects, i.e., people who participated in their experiment, were asked to choose between the two options, they expressed a preference for one. But when asked to state the amount of money which would be indifferent to each option, they reversed the order of the preference. This result upset researchers with normative mindsets so much that Grether and Plott (1979) carefully replicated the experiment,

taking into the account variables such as the cost of information processing, that would preserve transitivity. Not only were the original results confirmed, but no simple rational explanation could be found.

Apart from the above observed violation to the normative approach, challenges have also been made to the validity of four axioms underlying the normative approach: cancellation, transitivity, dominance and invariance. With carefully designed studies, Allais (1953) and Ellsberg (1961) first reported the violation of cancellation. Bell (1982) and Fishburn (1982, 1984) showed the violations of transitivity. Tversky and Kahneman (1988) did that for dominance and Tversky and Kahneman (1988) and McNeil et al. (1982) for invariance. Human psychological factors, such as framing (Kahneman and Lovallo 1993) and context dependent preference (Tversky and Simonson 1993), have been theorized as being the causes of such violations. Furthermore, Tversky and Kahneman (1988) show that most individuals violate the implications of the subjective expected utility model even in the simple choice situations where there are absolutely no uncertain or risky conditions.

Descriptive approach studies brought in evidence of people's real decision behaviors that violate the description of normative approach. Lichtenstein et al. (1978), Tversky and Kahneman (1973) and Kunreuther et al. (1978) all studied the ability of individuals to form subjective probabilities from objective ones. Using information gathered in the real world, Lichtenstein et al. (1978) analyzed individuals' judgments toward lethal events. They found that individuals consistently misjudged the frequencies

of these events by underestimating the high frequency ones and overestimating the low frequency ones, although the data regarding the objective frequencies of such well-known events were available to the public. In addition to misjudgment, Kask and Maani (1992) noted that individuals might *anchor* their subjective probability judgments to some levels regardless of available information about the objective probabilities. Tversky and Kahneman (1973) showed that individuals judge by the *availability* of heuristics and previous experiences. Furthermore, Tversky and Kahneman (1981) revealed that a subtle but critical issue used to be neglected — the framing effect. The normative approach states that if a choice is made from a set of alternatives, the choice should depend only on the membership in the set, not on how the set is defined. However, the lesson from the framing experiment is precisely that such a premise does not hold. The ways the choice questions are framed affect the choices to be made (see McNeil, Pauker, Sox and Tversky 1982).

Some researchers claimed that the violations of the normative approach, or more precisely the departure from a “rational” or “optimal” behavior could be overcome by increasing incentives through higher payoff and/or punishment. In one sense, this argument is irrefutable since one can always claim that the incentive is not high enough. However, direct evidence showed that increased payoffs do not necessarily eliminate such biases (Fischhoff, Slovic, and Lichtenstein 1977; Grether and Plott 1979). Indirect evidence from clinical judgment studies continued to show similar results (Dawes 1979).

Prospect Theory — A Descriptive Approach Theory

In light of the above research findings, a descriptive theory of an individual's decision behavior is needed. Tversky and Kahneman made a major attempt to formulate such an alternative theory. They argued that the deviations of actual behaviors from the normative descriptions are "too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative system" (Tversky and Kahneman 1988, p. 167).

Prospect theory is a descriptive theory that explains an individual's decision behavior (Tversky and Kahneman 1981, 1988). The theory distinguishes two phases in a choice process: the first phase of framing and editing and the second phase of evaluation. The phase of framing and editing reveals an important but typically ignored element. Because human knowledge of any particular object "is generally rich in content and complex in forms, it includes appearance, function, relation to other objects, and any other property of the object that can be deduced from our general knowledge of the world" (Tversky 1977, p. 329). Thus, the process of representing an object or alternative by a number of attributes or features depends on prior processes of selective attention and cue achievement. The significance of such a framing process lies in its influence over the problem evaluation in the second stage, possibly with completely different decisions (see McNeil, Pauker, Sox, and Tversky 1982).

Prospect theory superficially resembles the expected utility model in that it also involves a value function, decision weights and a compensatory combining rule.

However, the value function in the prospect theory differs from the utility concept in that: (1) it is defined by the deviation from a reference point rather than being defined over total assets; (2) it is concave for gains but convex for losses; and (3) it is steeper for losses than gains, i.e., the pain of loss is greater than the pleasure of winning an equal amount. The decision weights in prospect theory are not subjective probabilities. They reflect the impact of uncertainty on the evaluation of prospects and are transformations of the probabilities; they also have several important properties. For example, the sum of complementary decision weights does not sum to one (subcertainty), and small probabilities are overweighted. The prospect theory is able to explain most observed decision behaviors including those violations to the description of the normative approach.

Summary and Conclusion

The purpose of this chapter is to provide theoretical preparations for the model development taking place in the next chapter. The review contains three sections for this intent.

A brief review of the studies on the diffusion of innovations highlights the scope and typical methodology of the study. It outlines the perceptual framework of the theory of innovation diffusion by reviewing the five-stage model of innovation decision process and the five attributes of the diffusion of innovations.

Innovation diffusion models are reviewed next with emphasis on the relative merits of their modeling approaches. Although parsimonious, the aggregate approach models have their theoretical root in the models of epidemics. The modifications and extensions following this approach have been basically "piecemeal." Empirical support for such extended models has been inconclusive. The major limitation with aggregate approach models is the lack of theoretical guidance and consistence for the incorporation of decision variables. The micro approach models, on the contrary, seems to be promising approaches for the innovation diffusion models. By considering individuals' decision behaviors, they offer flexibility in handling the heterogeneity of a population and examining the impact of decision variables. The review of the models with this approach is based on the three essential steps for the development of such models, i.e., heterogeneity, uncertainty reduction, and aggregation. It calls for further examination of these three steps with a more appropriate and workable perspective.

To provide the rationale to adopt a descriptive approach to modeling the decision behavior under uncertainty, the third section briefly reviews the recent advancement on this subject. Besides the implementation, the validity of the normative approach can also be a problem concerning new product diffusion.

It is clear from the review that this study will take a micro approach to the modeling of new product diffusion. It will apply the descriptive approach to the modeling of individuals' decision behaviors.

Chapter 3

A Model of New Product Diffusion

The diffusion of a new product is basically a process of uncertainty reduction in a heterogeneous population. It “involves the adoption of the innovation by individuals in the relevant population. Adoption, in turn, involves deliberate choice decision on the part of the individual” (Chatterjee and Eliashburg 1990, p. 1057). The micro approach model to be developed has three significant features: (1) it employs product attribute theory to construct an analytical framework in which a new product, consumer heterogeneity and individuals’ decision behaviors are analyzed; (2) it adopts a descriptive approach to the decision making under uncertainty to yield a parsimonious model; and (3) it introduces a dynamic dimension for individuals’ decision behaviors that explains the progress of a diffusion process.

Product Attributes

Product Attribute Space

A consumer demands a product not for the sake of the product itself, but for the benefits conveyed by the product. This product attribute approach to consumer demand emerged from three major areas: psychology (e.g. Luce and Tukey 1964), economics

(Lancaster 1966, 1971; Rosen 1974) and marketing (e.g., Green and Srinivasan 1978). Economists have used this approach to enhance their study on product differentiation (see Eaton and Lipsey 1990; Lancaster 1990). Marketing researchers have used this approach extensively for the study of consumer behavior. Their efforts include quantitative measurements of consumer responses, e.g., multiattribute scaling and conjoint analysis, and new product concept generation and evaluation (Shocker and Srinivasan 1979). Extensive economic and marketing literature has provided both the theory of product attribute and the empirical support.

This study is concerned with the construction of an analytical framework for the innovation diffusion models based on the product attribute theory. Economics literature provides a means by which the analysis of consumer behavior in product space can be interpreted in the attribute space through such theory.³ According to microeconomic theory, a consumer chooses an optimal combination of n different goods, with price vector P , to maximize his/her utility under the budget constraint, I . The maximum utility level associated with his/her optimal choice can be expressed as

³ Characteristics, rather than attributes, have been used in the economics literature (e.g., Lancaster 1966) to describe the nature of products. Such characteristics refer to physical attributes. Marketing literature, on the other hand, considers physical as well as psychological attributes because both attributes affect consumers' behaviors. In fact, Crawford (1991) interpreted the meaning of product attributes at three different levels: (1) feature, physical level, (2) functional, and (3) benefit, usage level. The analysis of each of these three levels can be meaningful depending on the problem.

In this study, I use the term "attribute" to mean primarily the physical attribute of products, following the tradition of economics. However, the use of "attribute" here makes it conceptually ready for further extensions since I see that the analysis at other levels are all possible and profitable in the future.

$$U_i^* = U_i(X_{i1}^*, X_{i2}^*, \dots, X_{im}^*), \quad (3.1)$$

where X indicates the quantity of a good, and the superscript $*$ indicates the optimum by the individual i . Equation (3.1) can also be expressed equivalently as $U_i^* = U_i(I_i, P_1, \dots, P_n)$, a function of the income of individual i and the prices of relevant products. According to product attribute theory, a product may contain several attributes, and the same attribute may be furnished by several products. Lancaster (1971) defines consumption technology as a transformation matrix converting products from the product space into a relevant product attribute space. The optimal demand of a consumer for products in terms of quantities can be translated into his optimal demand for product attributes. Consequently, the maximum utility level can be expressed as

$$U^* = U^*(A_1^*, A_2^*, \dots, A_m^*), \quad (3.2)$$

where A_m^* (m : the dimension of relevant product attributes. *Note: $m \neq n$, where n stands for the number of products*) is the optimal level of the m th attribute preferred by this consumer. These m product attributes define an m dimensional space. Lancaster's (1971) notion about intrinsic groups makes it possible to reduce the dimensions to be studied. The intrinsic group is such a group of products that are close substitutes. The analysis of product attributes within one intrinsic group is not affected by the attributes of other groups. For example, the attributes of automobiles will not interfere with the analysis of

the attributes of food groups. As such, we can focus on a relatively small set of products attributes.

An individual consumer can be regarded as a point in m dimensional space. The coordinates $(A_1^*, A_2^*, \dots, A_m^*)$ indicate his/her optimal point, corresponding to the optimal attribute levels chosen by this individual. We must pay close attention to the notion of optimal point here. Such optimal point is the equilibrium choice of an individual consumer in the product attribute space. Although derived through Lancaster's consumption technology, it is more appropriate to interpret it in Rosen's framework. Rosen's study is concerned with the market equilibrium of consumer choice and Lancaster's focus is on the product efficiency frontier. The significance of such a distinction lies in the implementation, i.e., the way we measure and estimate the optimal point of an individual consumer. Since individual consumers choose different combinations of goods, they pursue different optimal levels of product attributes. Consequently, they take different optimal points in the attribute space. In aggregate, consumers can be regarded as a complex distribution of their optimal points in the attribute space as a result of their preferences and budget constraints.

In contrast to consumer distribution in the attribute space, a new product takes a single point in this space, corresponding to the attribute levels it carries $(A_1, A_2, \dots, A_m)$. This is particularly relevant in the context of new product diffusion where one new product is to be adopted by a population of individuals.

The Ideal Point Choice Model

The construction of a product attribute space provides an analytical framework for the study of consumer choice behavior. Consumer heterogeneity in preferences is obvious here because each individual consumer is located at a different place in such space. Shocker and Srinivasan (1974) suggested using *Weighted Euclidean Distance*, an ideal point version,⁴ to model an individual consumer's choice behavior. Denote w_k as the weight of the k th attribute assigned by an individual in his/her utility structure; A_k the location of the product on the k th attribute coordinate; and A_{ik}^* the location of individual i 's ideal point on the k th attribute coordinate. The *Weighted Euclidean Distance* between an individual and the location of a new product can be expressed as

$$d_i = \left(\sum_{k=1}^m w_k (A_{ik}^* - A_k)^2 \right)^{1/2} . \quad (3.3)$$

And his/her utility loss due to the existence of such distance, i.e., the product available not matching his/her ideal preference, can be expressed as

⁴ The meaning of ideal point by Shocker and Srinivasan is analytically the same as the optimal point we defined above. The ideal point can be regarded as the stated preferences of a consumer in an attribute space, and the optimal point can be regarded as the revealed ones.

Besides the ideal point version, researchers also suggested the vector version. The vector version models utility directly as a weighted sum of attribute levels of each alternative. Such specification is often seen in simple statistical models.

$$\Delta U_i(\text{distance}) = -(\text{weight})_i d_i^2 = -\sum_{k=1}^m \alpha_k (A_{ik}^* - A_k)^2, \quad (3.4)$$

where α_k is the overall weight an individual assigns to the k th product attribute in his/her utility structure. Since his/her utility level is in an inverse relationship with the squared Weighted Euclidean Distance, an individual obviously chooses a product that is the closest to his/her ideal point. Equivalently, when other factors are considered, an individual whose ideal point is closer to the location of a new product tends to buy it earlier.

A Note on Two Different Attributes

It is useful to differentiate two types of attributes and check their implications for this study. Economists describe these two attribute types as *horizontal* and *vertical* (Lancaster 1979; Shaked and Sutton 1983). An attribute is *horizontal* if perfectly informed consumers choose different levels of the attribute. On the other hand, an attribute is *vertical* if perfectly informed consumers pursue the same level of the attribute. One example of a horizontal attribute is the color of a car and its vertical counterpart is the quality of the car. The attribute of vertical nature can cause problems if we use the notion of ideal point as defined in most marketing literature. As all consumers will tell you that they want the highest possible quality, their ideal points collapse to the extreme level of such an attribute. Fortunately, this should not be a problem for this study. Although an individual consumer may prefer a higher level of quality, he/she may be

forced to choose a different level of such an attribute due to his/her budget constraint. The constraint assures that consumers will be distributed at different attribute scales, though some attributes may be of vertical nature.

Uncertainty

Uncertainty is caused by imperfect and incomplete information regarding an innovation or new product. We distinguish the concepts of imperfect and incomplete information. The information is imperfect if the information source itself is deficient. On the contrary, the information is incomplete if a consumer does not attempt to obtain the otherwise complete information for various reasons. Such information imperfection and incompleteness can be substantial when a new product is first introduced into a market, as discussed below.

The information regarding a new product is all too often imperfect, especially for novel products. The uses, reliability, sideeffects, and potential impacts of a new product are rarely known in detail at the early stages of the product life cycle. Such scenarios are real for not only general consumers, but also for engineering specialists. Examples of such new products include new pharmaceutical and high-tech products.

Consumers often do not obtain complete information on a new product realistically because information acquisition costs time, resource, and maybe expertise. This phenomenon has been subject to the study of the economics of information (Stigler 1961). Because of such cost, consumers are likely to make purchase decisions with

incomplete information. Imperfect and incomplete information cause uncertainties for consumers. Consumers counteract the uncertainties by learning in both active and passive ways.

We adopt a descriptive approach to modeling the effect of uncertainty reduction on a consumer's decision behavior. Following this approach, we employ a strength variable N , the cumulative number of people who have purchased the new product, to correlate with the changes of an individual consumer's utility level. The strength variable is directly related to the reduction of uncertainty. The relationship between N and uncertainty reduction, or ultimately the changes of a consumer's utility level, exists due to imitation effect, social pressure, and learning behavior. Imitation is a passive way to respond to an innovation. A consumer observes how others behave and responds accordingly (see Rogers 1983). From the perspective of the economics of information, such "irrational" behavior is a rational outcome when it is not costless to obtain information. Imitation is often the least costly way to learn. Previous actions taken by other people reduce the uncertainty and increase the individual's utility level. N thus gets into his/her utility function. Social pressure exerts influence on an individual's decision (see Granovetter and Soong 1983, 1986). Such pressure is correlated with the size of adoption population, too. This effect is consistent with the positive demand externality. Even active information seeking and learning behaviors are correlated with the cumulative adoption population size N as well. A new product in its early life stages needs to have bugs worked out. More information about its reliability, technical performance, and so forth will become available only after more consumers have used it.

Moreover, an individual may learn from survey statistics on how many people have purchased the new product. The descriptive approach takes into account both rational and irrational behaviors of a consumer. Of course, the reduction of uncertainty about a new product may reveal more discouraging information about the product so that a consumer's perceived benefits may decrease. Such an effect should be separated from the effect of uncertainty reduction. In general, the reduction of uncertainty by itself increases an individual's utility level. Such an increase in the utility level is caused by the so-called intrinsic value (Bell 1982) of uncertainty reduction.

Let the functional relationship between the changes of an individual's utility level and the adoption population size be $f(N)$. We expect $f(N)$ to be concave, i.e., $f'(N) > 0$ and $f''(N) < 0$ in light of the law of diminishing returns.⁵ In a power transformation family, this means a function form as $f(x) = x^\alpha$, where $0 < \alpha < 1$. Tversky and Kahneman (1991) and Kahneman and Lovallo (1993) employed such a functional form and determined that the value of α equals 0.576. This value satisfies the requirement for the law of diminishing returns. For analytical convenience, we round off α to obtain a power parameter $\alpha = 0.5$. We thus have the following relationship between an individual's utility level and the size of the adopting population,

$$\Delta U_i(\text{uncertainty reduction}) = f(N) = \beta \cdot \sqrt{N}. \quad (3.5)$$

⁵ As a common practice, $f'(N)$ denotes the first derivative of $f(N)$ with regard to N and $f''(N)$ denotes the second derivative of $f(N)$ with regard to N .

Equation (3.5) indicates that an increase in the adopting population size will enlarge the utility level of an individual. The parameter β is a measure of individual consumer's behavioral characteristics under uncertainty. It can be interpreted as the coefficient of size effect, i.e., the importance of N in the utility structure by an individual. Given some changes of N , the higher the β values, the greater the changes of an individual's utility level. In the context of innovation diffusion, β is expected to be a function of the following three attributes: complexity, trialability, and observability.

To study the dynamics of new product diffusion, an additional dimension is needed. This dimension is related to the changes of the strength variable. Under dynamic consideration, not only does the magnitude of the strength variable N affect the utility level of an individual, so does its volatility or changes. For example, besides the current income, the prospective changes of an individual's income level affects his/her utility level, too. A consumer who has a certain level of income but anticipates changes in his/her current income level is likely to end up with different utility levels. Since the strength variable N represents the cumulative adoptions, a stock variable, we can reasonably propose that a consumer's utility level is a function of the variability or changes of such stock variable, i.e., dN/dt . For an individual consumer under uncertainty, the changes of dN/dt in either direction mean variability and reduce his/her utility level (readers may refer to stock markets where changes in stock prices give rise to uncertainties, even though the overall price may be on the rise). The empirical studies by Meyer (1981) and Roberts and Urban (1988) concluded that perceived variances or

volatility adversely affect the utility level of an individual. Assuming a linear relationship between dN/dt and the utility changes of an individual, we have

$$\Delta U_i(\text{volatility}) = -f(dN / dt) = -\gamma \left| \frac{dN}{dt} \right|, \quad (3.6)$$

where γ is another measure of the consumer's behavioral characteristic under uncertainty and the $| |$ indicates the operation for an absolute value. We name it the coefficient of dynamic effect. It differs from β because it measures different dimensions of consumer behavior under uncertainty, emphasizing the decrease in utility level due to the volatility of the strength variable N . A higher γ value reflects a larger impact of volatility on the changes of an individual's utility level.

Parameters β and γ take, strictly speaking, specific values for each individual consumer because they are the measures of consumer's behavioral characteristics. The expected values can be used to study a population's behavior if the randomness in consumer valuation can be canceled out in the aggregation. Because new products differ in the nature of complexity, trialability, and observability, they present different values of β and γ for consumers. Such differences shape the diffusion patterns, or the market growth behaviors of the new products.

Individual's Adoption Decision Behavior

So far, we have examined two important components for developing a microapproach model of new product diffusion, i.e., preference heterogeneity and the impact of uncertainty reduction. The theory of the diffusion of innovations conceptualizes five phases for the innovation decision. A consumer goes through these phases to become a user of the new product. His/her decision can be modeled as the following.

Consider that at time zero a new product is introduced into a market. The product provides perceived relative advantages that are translated into an individual's perceived utility, U_i^{new} . The U_i^{new} should have taken into account the substitutive and complementary effects of the new product with other existing products. It also includes switching costs in order to adopt a new product. This value, of course, should be allowed to change over time as the values of new products are often augmented over time. Following the discussion in the previous two sections, we can write the net changes of an individual's utility level in an additive way as

$$\Delta U_i = U_i^{new} - \Delta U_i(\text{distance}) + \Delta U_i(\text{uncertainty reduction}) - \Delta U_i(\text{volatility}). \quad (3.7)$$

Since the model to be developed is for the explanation of aggregate diffusion of a new product, secondary effects could be dropped to ensure the focus on the primary effects. Heterogeneity in consumers' preferences has been reported to be much stronger than in their perceptions (Gatignon and Robertson 1986). Therefore, we can use

heterogeneous ΔU_i (*distance*) to represent the primary force of consumer heterogeneity while using the population mean U^{new} for U_i^{new} . Uncertainty reduction is captured by both size and dynamic effects. Individual effect can be treated as a population effect plus a random individual specific effect. Since individual randomness tends to cancel out at the aggregation, the population mean can be used here. We rewrite the above equation as

$$\Delta U_i = U^{new} - \Delta U_i(\text{distance}) + \Delta U(\text{uncertainty reduction}) - \Delta U(\text{volatility}). \quad (3.8)$$

The above equation implies that $\Delta U_i = 0$ is the status quo for the individual consumer i . If there is no new product, U_i^{new} equals zero, and three other terms on the right side are not relevant. $\Delta U_i = 0$, and an individual takes no action. An individual adopts a new product when ΔU_i is greater than zero. Therefore, we can state an individual's adoption behavior as follows:

$$\Delta U_i = U^{new} - \sum_{k=1}^m \alpha_k (A_{ik}^* - A_k)^2 + \beta \sqrt{N} - \gamma \left| \frac{dN}{dt} \right| \geq 0. \quad (3.9)$$

The Diffusion Frontier

The expression (3.9) can lead to an interesting phenomenon — *Diffusion Frontier* — if we look at it from the aggregate perspective. Consider a threshold situation when an individual is about to adopt the new product. Equation (3.9) can be written as

$$-U^{new} = -\sum_{k=1}^n \alpha_k (A_{ik}^* - A_k)^2 + \beta\sqrt{N} - \gamma \left| \frac{dN}{dt} \right| \quad (3.10)$$

The right side of (3.10) indicates an offsetting effect: A consumer's utility level decreases because his/her ideal point is not at the product location, but such utility loss is compensated for by the utility gain through the size effect less the impact of volatility. At the initial stage of new product diffusion, only those individuals whose ideal points are at or around the location of a new product adopt the product. They can be titled "innovators" by the terminology of innovation diffusion. These individuals need less compensation in their utility structure to counteract the impact of uncertainty and to adopt a new product. As the diffusion process progresses, the number of individuals who have adopted the product increases. Individuals whose ideal points are farther away from the product location now become adopters because they have gained more utility due to uncertainty reduction, which can offset the greater utility loss caused by the longer Euclidean Distance between their ideal points and the product location. This scenario suggests the existence of an orderly pattern in the diffusion process, a moving *diffusion frontier* in the

product attribute space. As the diffusion frontier expands, more and more consumers are included in the frontier and become adopters of the new product. The diffusion process ceases to progress when the marginal consumers at the frontier feel indifferent about adopting the new product.

A diffusion frontier can be identified by solving the trajectory of A_{ik}^* (for $k = 1, \dots, m$), a locus of ideal points of individual consumers, from Equation (3.10). In a two-dimensional space, we can easily show that the trajectory is usually an ellipse (see Appendix 1). The diffusion frontier expands farther along the dimension of the product

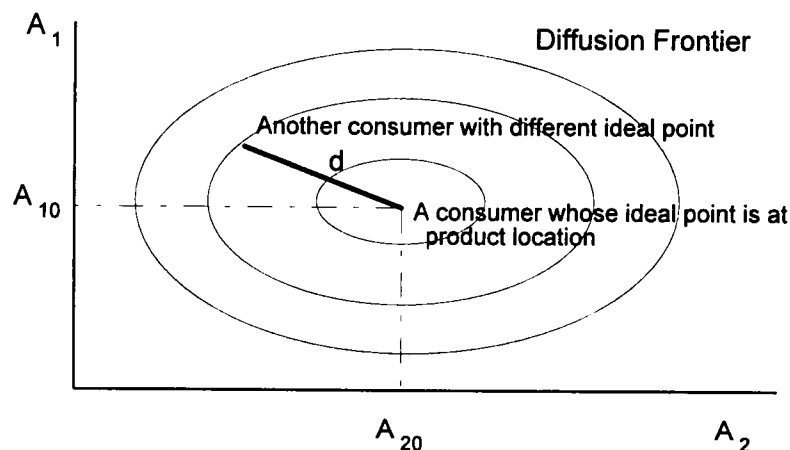


Figure 3.1 Diffusion Frontier

The diffusion of a new product takes place when the diffusion frontier expands over time from the product location. Individuals enclosed in a diffusion frontier are the adopters.
Note: a new product is located at (A_{10}, A_{20}) .

attribute with smaller salience. Since consumers are distributed across the attribute space, we can perform integration within the boundary of a diffusion frontier to find out the total number of adopters,

$$N = \iint_{\substack{\text{within} \\ \text{frontier}}} \rho \, dA_1 dA_2 \quad , \quad (3.11)$$

where ρ is the consumer density distribution, and A_1, A_2 are two attributes. If $\rho = \rho_0$, consumers being uniformly distributed in the attribute space, we can write (3.11) as $N = \rho_0 \pi ((A_1^* - A_1)^2 + (a_2/a_1)(A_2^* - A_2)^2)$, i.e., $N = \rho_0 \pi$ (the area within the ellipse diffusion frontier). This result provides a connection between N and A_1^*, A_2^* at the diffusion frontier. If we compress the scale of one attribute so that $\alpha_1 = \alpha_2 = \alpha$, a simpler expression can be obtained. The total adopters N is the product of ρ_0 by the area of a circle, or $N = \rho_0 \pi ((A_1^* - A_1)^2 + (A_2^* - A_2')^2)$, where ' indicates that the scale of axis 2 is altered. ρ does not have to be constant. If ρ is not uniformly distributed, the integration should be performed directly according to (3.11) to establish the relationship between N and attribute levels. For analytical clarity, the following study is based upon the assumption that ρ is constant. The uniform distribution of consumer density on a attribute scale is commonly assumed in analytical models regarding product differentiation (e.g., Eaton and Lipsey 1990).

A Diffusion Equation at the Market Level

The diffusion of a new product at market level can be obtained by aggregating individuals' adoption behaviors. The aggregation in this section is analyzed in a two-dimensional attribute space. The reason to choose a two-dimensional space is to make analysis succinct while reserving the richness of the multiattribute perspective. High dimensional situations can be extended easily.

By substituting the result of (3.11) into (3.10) to cancel out the Euclidean Distance term, we can obtain a differential equation for new product diffusion at the aggregate level,

$$\frac{dN}{dt} = \frac{U^{new}}{\gamma} + \frac{\beta}{\gamma} \sqrt{N} - \frac{\alpha}{\pi \rho_0 \gamma} N. \quad (3.12)$$

The absolute operation in the above equation is removed after the sign on the right-hand side is considered. The definitions of the variables in (3.12) are the same as in previous sections.

Equation (3.12) is similar to the well-known Bass model (1969). The dN/dt represents the rate of diffusion, or the sales of new products in a particular time period. It contains two terms related to the adoption population size N , although the power parameters are different from that in the Bass model. However, (3.12) has one fundamental difference from the Bass model. The model parameters in (3.12) can be interpreted and measured based on individuals' behaviors and perceptions. If these

parameters can be obtained for a new product yet to be introduced, (3.12) can be used to perform the pre-launch forecasting. The theoretical framework of (3.12) is well founded. It offers rich implications for the analysis of the impact of consumers' behavioral and decision variables on the patterns of new product diffusion.

Model Properties: A Simulation Study

A simulation study can be conducted to understand the impact of model parameters, i.e., consumer behavioral and decision variables, on the patterns of new product diffusion. Such an analysis is needed because the differential equation (3.12) is nonlinear and does not have a closed-form solution. Besides, the simulation can help in visualizing the dynamic changes of new product diffusion patterns due to changes of consumer behavioral and decision variables. The diffusion of a new product is a dynamic process. The increase of sales in early stages does not necessarily mean that later sales will follow suit. If the ultimate market potential remains the same, shifting the peak time of new product sales simply causes more sales in one period but fewer sales in the other. Such a dynamic relationship is better presented by simulation and graphs.

Let us first define a base pattern of new product diffusion with Equation (3.12). It will serve as the standard for comparison purposes. Let U^{new}/γ be the perceived utility level after the uncertainty adjustment, named u ; β/γ the coefficient of size effect after the uncertainty adjustment, named β ; and α/γ the coefficient of weight effect after the

uncertainty adjustment, named *alpha*. The base values for *u*, *beta*, and *alpha* are chosen at 200, 200, and 0.3, respectively.

The impact of four variables and parameters will be evaluated independently. They are *u*, *beta*, *alpha*, and γ . γ is included because it is an important model parameter embedded in three other parameters. A separate simulation study of it will provide us with valuable insight on how it affects the diffusion patterns. The results of the simulation study are reported in Figures 3.2-3.5.

Let us first look at the impact of *u*. Since $N|_{t=0} = 0$, *u* in the proposed model indicates the initial sales at time zero. According to Mahajan, Muller, and Srivastava (1990), this value identifies the volume of innovators. It becomes clear from our model that the number of innovators is proportionally related to the perceived relative advantages of a new product. The managerial implication is that firms should improve their products and make them well understood and perceived by potential consumers. The more relative advantages a new product has, the more innovators or initial sales it will generate. The simulation also demonstrates the take-off phenomenon well-known in the study of innovation diffusion. When *u* is very small, as shown when $u=2$, the diffusion takes place initially at a very slow pace. The diffusion rate then picks up due to the nonlinear nature of the model. It can be shown that *u* does not affect the market potential very much when the condition $(\beta\pi\rho_0/\alpha)^2 \gg 4\pi\rho_0 U^{new}/\alpha$ is satisfied. Its primary effect is to shift the peak time of the diffusion curves to sales patterns, as shown in Figure 3.2. The diffusion pattern under this scenario agrees with the findings by Kamakura and

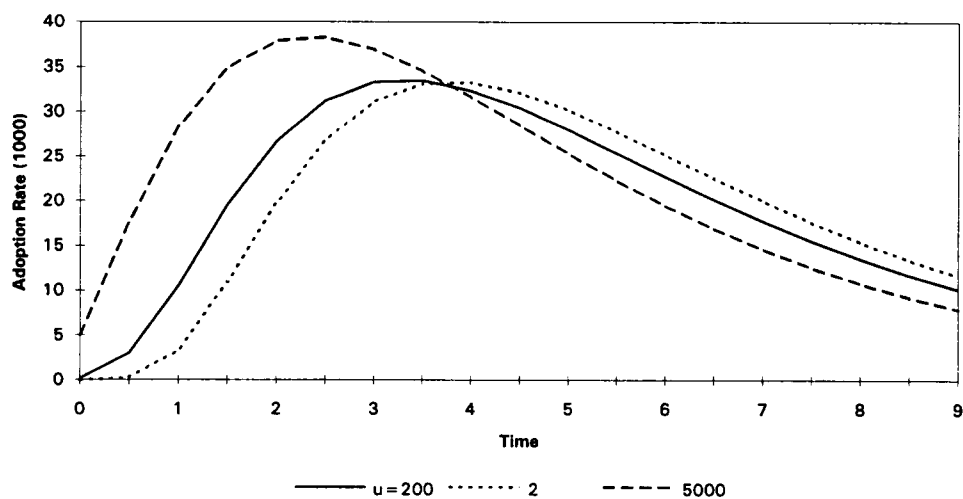


Figure 3.2 The Impact of Risk-Adjusted Relative Benefits u on Diffusion Patterns

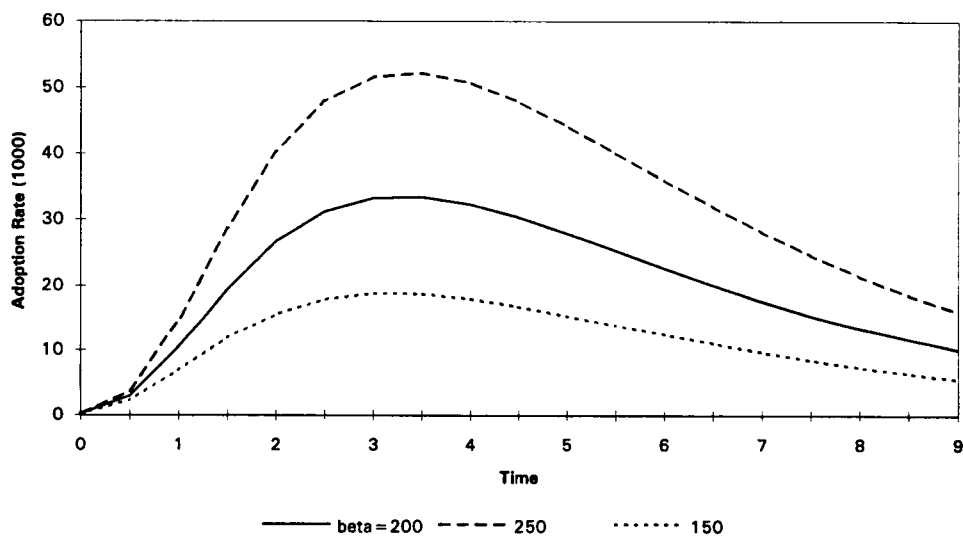


Figure 3.3 The Impact of Risk-Adjusted Size Effect β on Diffusion Patterns

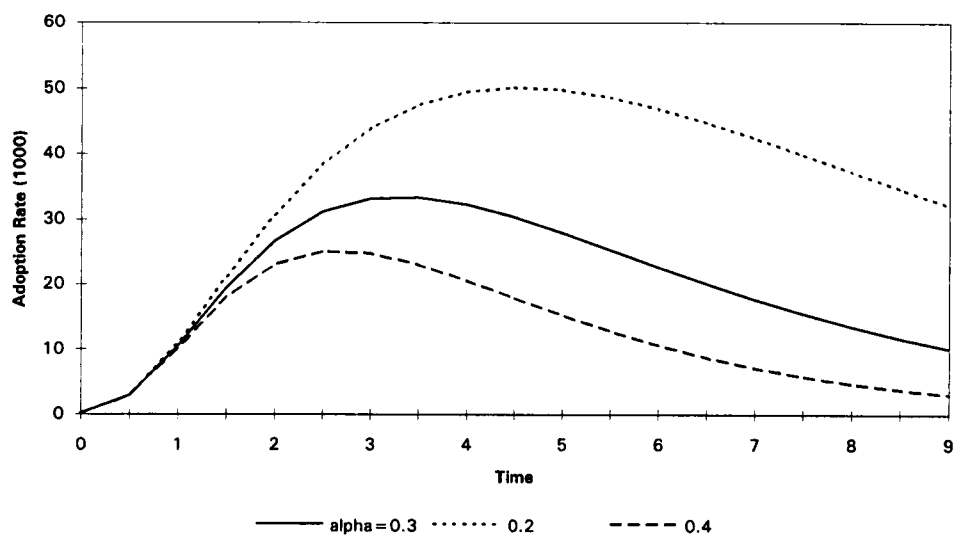


Figure 3.4 The Impact of Risk-Adjusted Attribute Weights α on Diffusion Patterns

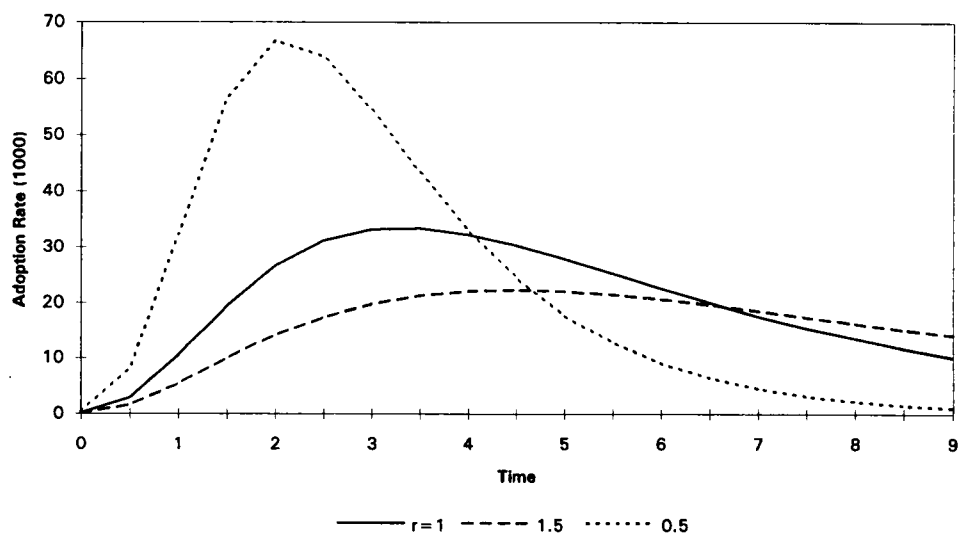


Figure 3.5 The Impact of Risk-Adjusted Dynamic Effect γ on Diffusion Patterns

Balasubramanian (1988) that price affects the diffusion rate rather than the potential market size of a new product. However, there exists the possibilities that u becomes so big that it could play a significant role in determining both the rate and the size of the diffusion of a new product when the condition $(\beta\pi\rho_0/\alpha)^2 \gg 4\pi\rho_0 U^{new}/\alpha$ no longer holds. Given that the price is closely related to the u , the above simulation results help explain the controversy concerning whether the price of a new product affects the diffusion rate or the market potential.

Network effect or demand externality can affect the diffusion of a new product. Such an effect can be easily accommodated by the proposed model through the consideration of variable u . Because the network effect or demand externality is typically modeled as a function of the number of adopted users, u thus will contain an N -dependent component. This component can be separated for analytical purposes. Its impact can be treated equivalently to influence the value of size effect or dynamic effect, which shapes the patterns of new product diffusion.

The diffusion pattern is very sensitive to the changes of β , α , and γ . A small variation in β or γ will cause significant changes in the pattern of new product diffusion. As shown in Figures 3.3 and 3.5, β affects the magnitude of the peaks, and γ affects the timing of the peak of a diffusion pattern. The Figure 3.4 shows that the salience or the weights of product attributes an individual assigns in his/her utility structure greatly impacts the patterns of new product diffusion. Though smaller product attribute salience leads to a higher market potential, it does so by the delayed peak time

because the diffusion frontier has to take time to expand farther out in order to include more potential adopters. The salience of attributes does not affect the rate of diffusion so that initial adopters do not differ due to different α values. In a word, a smaller α value causes the diffusion of new products to peak later but with a higher market potential. These properties can help build testable hypotheses for the diffusion of new products.

Discussion: The Distribution Issue

The derivation of Equation (3.12) is grounded on two assumptions with regard to the consumer distributions in a product attribute space. They are the uniform distributions of consumer density and their perceived relative benefits of a new product. Although these assumptions serve the analytical model well, the relaxation of them can bring more insight to the model.

Uniform density distribution of consumers in an attribute space has been an approximation. Although the distribution in such space is expected, no empirical study has been conducted. Consumers are known to be distributed along the income scale; but the distribution patterns can be quite different from that in an attribute space. Surveys and analyses of secondary data can be used to estimate such distributions empirically.

It is important to indicate that ρ in the model represents the density of those consumers who are aware of the product and are potential adopters. The literature of innovation diffusion identifies five stages for the decision process. Further analysis can utilize the survey results to include the evolution of such stages among consumers.

The uniform distribution of U^{new} has been made based on the fact that heterogeneity in perception is less important than that in preference. Such restriction can be lifted to accommodate more realistic situations. For example, the value of U^{new} can change over time because a new product performs better and/or consumers find more uses of it and thus value it more, or vice versa. The variation in U^{new} can also accommodate the heterogeneous consumer valuation across the attribute space. The heterogeneous distribution of U^{new} in the attribute space can be the result of consumer segments and/or product competition. The consideration of such distribution can facilitate the analysis of new product diffusion under competition. In the next chapter, an empirical study will be made regarding U^{new} as a function of the price of new products and consumers' income. It will attempt the first issue, i.e., the impact of changing U^{new} on the diffusion of new products.

Discussion: The Stochasticity Issue

Equation (3.12) represents a deterministic model of new product diffusion. Justification must be made regarding the decision to ignore the stochastic issues in the modeling. At first sight, the stochastic issue is inevitable because an individual's decision to adopt an innovation is stochastic and because the model built at the micro level should reflect such stochasticity. However, as we have noted before the development of the model, the focus of this study is to derive an aggregate diffusion equation based on the examination of individuals' decision behaviors. Statistical principles apply here: The

relative fluctuation of a population falls rapidly as the size of the population grows. The randomness at the individual level tends to cancel out as more individuals are included. Therefore, the stochasticity in individual decisions is only implied in (3.8) but not explicitly expressed in (3.12).

The model development has focused on the impact of two major forces in the diffusion of innovations, i.e., population heterogeneity and uncertainty reduction. Such two forces have been well recognized in the extensive studies of innovation diffusion.

Summary

A microapproach model of new product diffusion has been developed in this chapter. The scenario of the study is a new product to be adopted by heterogeneous individuals. The model development utilizes the product attribute theory to construct a multidimensional attribute space in which the preference heterogeneity of consumers, their choice behaviors, and the consequent diffusion of a new product are analyzed. A descriptive approach to decision behavior under uncertainty is adopted. It has been beneficial for deriving a parsimonious model.

An innovation diffusion equation is derived based on the aggregation of individuals' decision behaviors. It is analytically similar to the well-known Bass model but offers the advantage that the model parameters are composed of consumer perceptual and behavioral variables. Therefore, this model can be used to analyze the impact of such

variables on new product diffusion. It is methodologically appropriate to use this model for the pre-launch forecasting of the market growth of new products.

The model development has led to the concept of *Diffusion Frontier* in the multidimensional product attribute space. It provides a vivid depiction of the process of new product diffusion with intuitive implications for management.

The impact of consumer perceptual, behavioral, and decision variables on the patterns of new product diffusion is examined through simulation studies in this chapter. The results indicate that the relative perceived benefits of a new product have a nonlinear relationship with its market potential. When it is low, it affects only the diffusion rate but not the market potential of the product. When it is high enough to meet a certain condition, it will affect both the diffusion rate and the market potential. The salience of product attributes seems to be inversely related with the market potential of the product. Consumer behavioral parameters, as measured by the size effect and dynamic effect, have great impact on the diffusion pattern of a new product.

Chapter 4

Empirical Results

This chapter presents an empirical study on the model developed in the last chapter. The study has two purposes: (1) to validate the model specification and (2) to examine the impact of new product price and consumer income on the diffusion of new products. The Box-Cox transformation is employed to estimate the flexible functional form for model variable U^{new} . The study is not intended to be a full-scale application.

The Methodology

Scope

It is useful to first define the scope of the empirical studies because the model developed in the previous chapter is fairly comprehensive. A complete empirical study would involve the survey and estimation of consumer distribution, their valuations of a new product, and behavioral parameters under different dimensions of uncertainty, with each part being an independent topic. Time and resources prevent the author from conducting such a large-scale study. The focus of this empirical study is therefore practically placed on the validation of the model specification as described by (3.12).

Equation (3.12) includes a square root term resulting from the size effect. Such a square root term is unique to this model. Therefore, the first concern is the performance of the model with such a square root term. The model also contains the perceived relative benefit of a new product U^{new} , which is a sensible term used to consider the impact of new product price and consumer income. The empirical study is interested in examining the effect of price and income through U^{new} and whether such specification is more advantageous than the previous models. The implementation of the model will be discussed later in this section. The validity of the model can be established if we can obtain a higher R^2 value without sacrificing the significance level of the parameters to be estimated.

Unit of Analysis

The nature of innovation diffusion models requires that the unit of analysis be the physical unit of sales due to the first purchase. Replacement purchases should be excluded from the total sales for the appropriate analysis of new product diffusion. The study on replacement sales is an important but separate topic.

Product category or class is commonly used as the unit of analysis, e.g., all color TVs, all VCRs, all personal computers, or all microwave ovens, no matter what brands or generations they are. However, Norton and Bass (1987) demonstrated clearly that the generations of a product class, i.e., 4K, 16K, 64K, and 256K RAMs, exhibit strong diffusion patterns or product life cycle phenomena. On the other hand, Heeler and Hustad

(1980) indicated that the success of the Bass model was not repeated in the international setting. The diffusion patterns in other countries failed to follow the patterns described by the Bass model. Therefore, the success of the Bass model was attributed to the judicious choice of situation, population, and time frame (Bernhardt and Mackenzie 1972).

Any approximate answer to the above ambiguity is beyond the theoretical guidance of the Bass model because it is built at the aggregate level with great simplifications. The model developed in this study provides some clues to the answer, which comes from the consideration of consumer behavioral and decision variables in the model. As demonstrated by the simulation, the changes of these variables can dramatically regulate the diffusion patterns. Typical model estimation assumes the model parameters to be non-stochastic. Such condition can be satisfied only when the behavioral and decision variables do not change much during the course of new product diffusion. The level of product classification at which the variability of these parameters are relatively stable identifies the appropriate unit for analysis. Therefore, a product brand or generation will be a good candidate for the unit of analysis if the relevant consumer behavioral and decision parameters do not change significantly within the time frame of new product diffusion. On the other hand, a product category or class will be a good candidate for the unit of analysis if such parameters change significantly at the brand level but not at the category level. There is still the possibility that these parameters will change dramatically at the product category level, e.g., the case of personal computers. It is likely that even the product category cannot serve as an appropriate unit of analysis.

A product class or category is composed of brands and generations. A lesson from Norton and Bass's research (1987) is that the market growth of a product category can be studied through the market growth behavior of its generations. Summing up the growth of all generations of RAMs, we can obtain the market growth for the RAMs. The summation shows that the market growth of the RAM category is still at the rapid growth stage.

This empirical study uses the sales data of color TVs and VCRs at the product category level as the unit of analysis. Since both color TVs and VCRs have experienced significant product improvement and modifications, consumer parameters are expected to have changed significantly. It renders the product brand or generation level an improper unit of analysis. No reported analysis took place at that level. Rather, the analysis was done at the product category level. However, previous studies did not include extended years even though data were available for some products. For example, the first-purchase sales data of color TVs can be retrieved up to 1979. If we take product category as the unit of analysis, it is appropriate to treat whole households as the relevant population. Statistics show that it took fifteen years for color TVs to diffuse into half of the U.S. households. Therefore, it is not appropriate to study the diffusion of color TVs with sales data only up to around 1970 when the first sales peak appears.

The Model Implementation

The model for empirical validation can be written based on the diffusion Equation (3.12) as

$$S = \frac{dN}{dt} = \alpha_0 + \alpha_1 U^{new} + \alpha_2 N^{1/2} - \alpha_3 N + \varepsilon, \quad (4.1)$$

where α 's substitute all the parameters in (3.12), and ε is assumed to be a well-behaved random variable representing the disturbances due to individual sources. N is the cumulative first-purchase sales of a new product, and S is the current first-purchase sales of the product. Since the purpose of the validation study is not to infer the innovators or imitators, α 's are only treated as model parameters.

All functional forms of model variables are determined under the model assumptions except the term U^{new} . U^{new} is the perceived relative advantages of a new product. Its value is expected to be affected by not only new product price and consumer income, but also other variables such as the technical advancement of new products, their compatibility with other products and so forth. Due to the difficulties in obtaining these technical data at the current stage, this study considers only the effect of income and price.

For comparison purposes, we first set up a base model that is analytically equivalent to the Bass (1969) model. The validation study is conducted in two phases. By temporarily ignoring the influence of U^{new} in (4.8), we obtain the proposed model one. The purpose of this model is to examine the validity of the square root term. In other

words, the inquiry is about how the model with such a square root term performs when compared to the base model.

When the variation of U^{new} is taken into account, the proposed model can be used to examine the impact of price and income on the diffusion of new products. The full equation (4.8) serves as the proposed model two. It is obvious that both new product price and consumer income affect U^{new} according to economic principles. The increase in the price generally reduces the utility level of a consumer and the increase of a consumer's income generally increases his/her utility level. Average price of a new product can be used as the price variable for the examination of its impact on the market growth of a new product in a population. Per capita income can be used as the income variable, a measure of an average consumer's capability to buy a new product. Let us further assume that U^{new} is some kind of function of the income price ratio, i.e., *income/price*. Such specification considers the changes in real purchasing power of individual consumers. As indicated in recent publications of the Electronic Industry Association and the Home Appliance Manufacturing Association, the consumers' ability to buy new electronic products has increased over the years by the measure of their earnings over product prices. Therefore, dividing income by price provides a more appropriate measure than just deflating new product price itself for the change of a consumer's utility level. One question remains: how to determine the appropriate functional form of U^{new} . We adopt the Box-Cox transformation for this task, which will be discussed next in detail.

The maximum likelihood method will be applied to estimate the proposed models. The estimation procedure first determines the optimal value for the power parameter of the Box-Cox transformation. After obtaining such value, we can either apply the OLS method to the transformed model or estimate the original model with the maximum likelihood method.

The Rationale for the Box-Cox Transformation

The implementation of the model presents a challenge for the determination of the functional form of U^{new} . Three estimation techniques suggested in previous studies do not suit the need for estimating a flexible functional form here.

A Brief Look at Previous Estimation Methods for New Product Diffusion Models

The OLS method was first used by Bass (1969). It applies if we create a discrete analog to the continuous differential equation of new product diffusion. Since the number of nonadopters at time t_{i-1} is $m - N(t_{i-1})$, the expected number of incremental adopters, $X(i)$, in the interval (t_{i-1}, t_i) is given by

$$E(X(i)) = \left(p + \frac{q}{m} N(t_{i-1})\right)(m - N(t_{i-1})), \quad (4.2)$$

The interval is commonly chosen as a year since yearly sales data are generally available. The parameters p , q , m in the above equation are coefficient of innovation, coefficient of imitation and the market potential. They can be estimated by applying OLS procedure to the following equation:

$$\begin{aligned} X(i) &= pm + (q - p)N(t_{i-1}) - \frac{q}{m} N^2(t_{i-1}) + \varepsilon(i) \\ &= \alpha_1 + \alpha_2 N(t_{i-1}) + \alpha_3 N^2(t_{i-1}) + \varepsilon(i) \end{aligned} \quad (4.3)$$

After the parameters α 's are estimated, the values of p , q , m can be uniquely determined.

OLS method is easy and straightforward to use. However, the method possibly suffers from multicollinearity. Besides, the method can cause certain biases due to the use of a discrete analog to estimate the parameters of a continuous equation.

The Maximum likelihood (ML) method was proposed by Schmittlein and Mahajan (1982). It requires the knowledge of the cumulative function of a diffusion equation. Let M be the size of a population; the expected number of eventual adopters is $m=cM$. An unconditional cumulative distribution function can be written as

$$G(t) = \frac{c(1 - e^{-(p+q)t})}{1 + \frac{q}{p} e^{-(p+q)t}} \quad (4.4)$$

The likelihood function for the observed histogram up to $T-1$ time intervals for which the data are available can be written as

$$l(p, q, c) = (1 - G(t_{T-1}))^{X(T)} \prod_{i=1}^{T-1} (G(t_i) - G(t_{i-1}))^{X(i)} \quad (4.5)$$

where $X(T) = M - X(1) - X(2) \dots - X(T-1)$.

Although having corrected the time-interval bias, the ML method still leaves out other sources of errors. The obtained parameter estimates therefore may be too optimistic (Srinivasan and Mason 1986). Moreover, the estimation procedure involves searching, which may be sensitive to the starting values and lead incorrectly to a local optimum instead of a global optimum.

The Non-Linear Least Square (NLS) method was proposed by Srinivansan and Mason (1986). The idea behind this method is that the total adopters within time interval (t_{i-1}, t_i) can be expressed as the difference of cumulative adopters before and after that interval. This approach does not require the discrete analog but, like the ML method, requires a cumulative function. When we let $X(i)$ be the number of adopters in the i th time interval (t_{i-1}, t_i) and $F(t_i)$ the cumulative adoption at time t_i , we have

$$X(i) = m[F(t_i) - F(t_{i-1})] + \varepsilon_i \quad (4.6)$$

where ε_i is an additive error term. Substituting $F(t)$ with the cumulative distribution function, (4.6) becomes

$$X(i) = m \left[\frac{1 - e^{-(p+q)t_i}}{1 + (q/p) \cdot e^{-(p+q)t_i}} - \frac{1 - e^{-(p+q)t_{i-1}}}{1 + (q/p) \cdot e^{-(p+q)t_{i-1}}} \right] + \varepsilon_i . \quad (4.7)$$

Its estimation can be complicated, reportedly done with the biological analysis software BMDP. The procedure involves searching and inherits the same shortcomings as found in the ML method, i.e., slow convergence and possibly missing of the global optimum.

It is obvious that the improvements in estimation methods are made at the cost of computational complexity. Besides, the requirement for a cumulative distribution can be a big burden when a diffusion equation is not as simple as the benchmark Bass model. Such is the case for our model, which does not have a closed form solution. In addition, the proposed model contains a flexible functional variable U^{new} . This calls for a different method of estimation. We adopt the Box-Cox transformation for such purpose.

The Box-Cox Transformation

The Box-Cox transformation is an econometric/statistical method especially suitable when the relationship among variables is not theoretically given. It is powerful, for example, when estimating hedonic price functions: “The fact that economic theory places few restrictions on the form of the hedonic price function has led most researchers

to use a goodness-of-fit criterion in choosing an appropriate form for the hedonic function” (Cropper, Deck, and McConnell 1988).

Although Box and Cox (1964) initially proposed this power transformation only on the dependent variable in an attempt to restore the normality assumption, such transformation has been used extensively beyond its original scope. It now includes the transformation on independent variables as well. The major uses of such transformation have been to evaluate a prospect model specification and to identify appropriate functional forms.

The basic scheme of Box-Cox transformation can be written as

$$X_i^{(\lambda)} = (X_i^\lambda - 1)/\lambda \quad \text{where } \lambda \in (-\infty, \infty), \quad (4.8)$$

for all positive X s. The $X_i^{(\lambda)}$ above is the transformed variable, and λ is the power parameter. By choosing different values of λ , we can obtain a wide range of functional relationships between the transformed variable and the original variable X within the power family series. A linear relationship with X can be obtained by setting λ equal to one. A logarithm relationship with X can be obtained by setting λ equal to zero.⁶ A reciprocal relationship with X can be obtained by setting λ equal to -1 and so forth.

⁶ When λ approaches zero, (4.8) is not defined. However, L'Hospital's rule can be applied to solve the dilemma, and (4.8) can practically be treated as a continuous transformation.

There can be a full-scale or limited-scale application of such transformation. A full-scale application requires independent transformations of all model variables. A limited application transforms only selected model variables or imposes a same power parameter on all model variables to be transformed. The choice depends on the problem defined. The limited transformation models that equalize power parameters are used extensively in recent research (e.g., Bolton 1989 for the price elasticity estimates at the retailer level; Atkinson and Halvorsen 1990 for the valuation of life in automobile markets; Chang and Yu 1991 for the detection of varying demand elasticities for residential electricity).

In this study, the transformation is made with the variable U^{new} . A general functional relationship between U^{new} and the income price ratio can be written as $U^{new} = f(\text{income} / \text{price})$. If such a functional relationship is assumed within the power family, the relevant Box-Cox transformation (let $U = \text{income}/\text{price}$) can be written as

$$U^{new} = U^{(\lambda)} = \frac{U^\lambda - 1}{\lambda} . \quad (4.9)$$

The optimal value of λ and the appropriate functional form will be determined by data in empirical studies.

Data

A Brief History of Color TVs and VCRs

The experiment on color TVs receivers, i.e., color TV set in early days and simply color TV nowadays, and pilot sales started around 1950. The early standard for color TVs was incompatible with that for black-and-white ones already in the market. In 1953, a compatible new standard was proposed by NTSC (National Television System Committee) and selected by the FCC. In 1964, as the result of federal legislation to aid ultra-high frequency broadcasters (channels 14 through 83), the industry incorporated all-channel (VHF and UHF) tuners in all TV productions.⁷ Despite the added costs of these components, rapid technological advance did not cause a television price hike. In fact, real prices have been consistently decreasing. Such price decrease has helped the diffusion of color TVs. In 1963, associations of consumer appliances manufacturers and retailers began to compile sales data of color TV receivers. It took fifteen years for half of the U.S. households to have at least one color TV receiver. As of January 1989, the saturation rate of color TVs in the United States reached 95%.⁸

For many years, the conventional television set served one purpose, i.e., the reception and reproduction of broadcast programs. Useful features were gradually added and became standard, such as remote control, stereo sound, and close captioning. Big-screen direct-view TVs and projection TVs replaced the older version, medium-sized

⁷ Source: *Standard and Poors' Industry Survey*, yearly issues.

⁸ Source: *Electronics Data Book*, an EIA, Electronics Industrial Association, publication, 1990.

ones. Portable and pocket-sized TVs with Liquid Crystal Displays (LCDs) were also introduced. With the application of digital signal processing technology to TV receivers, the age of advanced television has begun. The future generation of color TV — High Definition TV (HDTV) — is expected to offer photo-quality pictures. The technology associated with such development has broad implications for communication and information processing.

Video cassette recorders, or VCR, were introduced in 1975. They enable viewers to record TV programs off the air for subsequent playbacks. In the early days, VCRs were virtually all made in Japan and carried a retail price of \$600-\$1500. Two Japanese companies, Matsushita and Sony, were responsible for two different formats used in video recording, Beta and VHS. They then licensed American companies to market the machines and licensed other Japanese companies to produce them.

Many features added to VCRs such as hi-fi stereo, picture-in-picture, slow motion and/or freeze. The camcorder, a one-piece camera-VCR combination appeared in the market during mid-1980s and gave added power to VCRs. As of January 1989, the saturation rate of VCRs in the United States reached 61%. Some 73 percent of all U.S. TV households also contained a VCR. As was the case with color TVs, there was a strong demand for second-time buyers who were seeking replacement or adding a second or even third VCR to their homes.

Video hardware, including TV receivers and video recorders and players, is a growing category of consumer electronics. It is expected to keep such trend due to high demand in the information age.

The Data

The first-purchase sales data of color TVs from 1963 to 1978 are calculated from the *Merchandising* journal, a weekly then monthly publication by the Association of Consumer Appliances Retailers. The journal is a detailed data source for major consumer durable product sales in the early years, including color TVs. It contains total sales in both unit and dollar measurements and also reports sales due to replacement and repeat purchases. First-purchase sales can be derived by subtracting replacement and repeat sales from total sales. However, the nature of the data for publication changed around 1980 due to increasingly more and diversified consumer new products. The data regarding first-purchase sales are no longer published. For this reason, the first-purchase sales data of color TVs up to 1978 are used in this study.

The sales data for VCRs are drawn from *U.S. Consumer Electronics Industry in Review*, a publication by EIA, Electronic Industry Association. Due to rapid expansion of product families, lines, and brands, the details of the sales data have been greatly reduced. First-purchase sales can no longer be inferred from the published sources. Although sales data for VCRs were likely to be contaminated by repeat and replacement purchases,

researchers (e.g., Bayus and Carlstrom 1992) treated the data before 1989 as if they were first-purchase sales. The study follows this convention.

The price variable used in the study is the average price of the product. It is obtained by dividing the dollar shipments in a particular year by the unit shipments in that same year. The average prices for color TVs and VCRs are plotted in Figures 4.2 and 4.3 on page 84.

The income variable used in this study is per capita disposable income. It is drawn from the *Economic Report of the President*. The current dollar value of the per capita disposable income in U.S. from 1960 to 1990 is plotted in Figure 4.1 on page 83.

Results

The results of the validation study with color TV and VCR sales data are listed in Tables 4.1 and 4.2, on pages 85 and 87 respectively. The performances of three candidate models are compared. The comparisons of model fittings are plotted in Figures 4.4 and 4.5, on pages 86 and 88 respectively. While model 1 examines the validity of the basic model specification of the proposed model, model 2 emphasizes the additional effect of U^{new} .

The Performance of the Proposed Model with a Square Root Term

The square root term of N in the model is the result of the general description that the size effect has a diminishing result on an individual's utility level due to uncertainty

reduction. It is unique to the proposed model. For this reason, we compare the model performances between model 1 and the equivalent of the Bass model.

The performance of model 1, with long-term, first-purchase sales data of color TVs is significantly better than that of the equivalent Bass model. The R^2 value of model 1 is 0.7001 vs. 0.4544 for the equivalent of the Bass model. The parameter estimates for both models are significant at the 1% level. Considering that the first-purchase sales data of color TVs are not contaminated by the replacement and repeat purchases, the improvement of model 1 over the basic model is credible. This can also be demonstrated by Figure 4.4. The plot of model 1 shows that it catches the general trend of the diffusion of color TVs. On the contrary, the basic model fails to do so due to its symmetric nature, which has been contended by flexible diffusion models that we have reviewed in Chapter 2.

The performance of model 1 regarding sales data of VCRs is relatively poorer than that of the basic model. The model R^2 dropped from 0.9905 for the basic model to 0.9387 for model 1. All model parameter estimates are significant at the 1% level. However, the less satisfactory performance of model 1 may result from both the contamination of the data and insufficient length of the data series. Because first-purchase sales data can no longer be inferred from the published sources, researchers have used the sales data up to when first-sales peak appears as the proximate for the first purchase sales. Even though the basic model performs better than model 1, its validity can be questioned. If we take a look at Figure 4.5, we can easily see that the basic model overshoots the peak

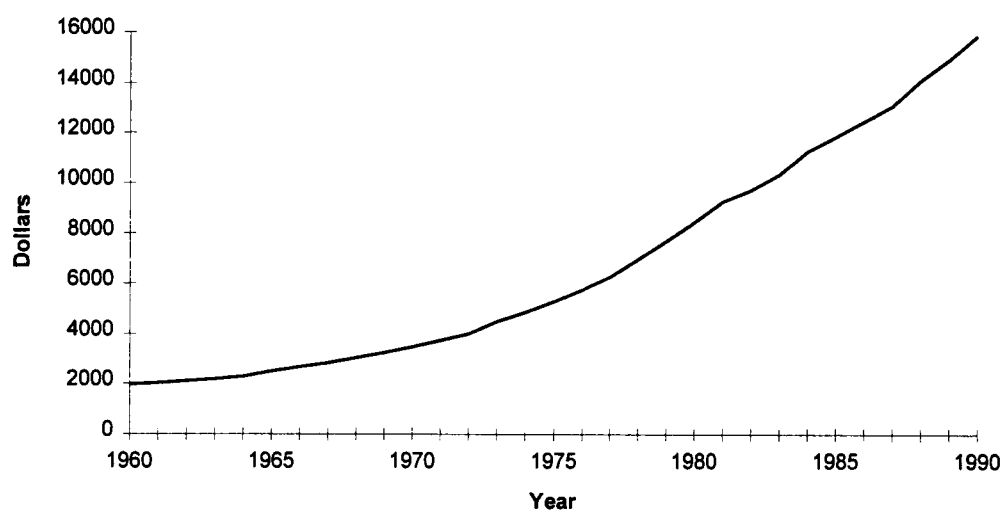


Figure 4.1 Per Capita Disposable Income in the U.S.
(1960-1990 in current dollars)

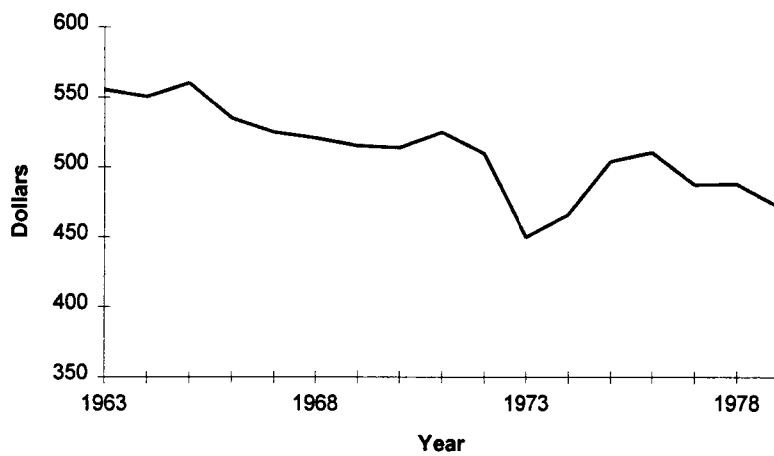


Figure 4.2 The Average Price of Color TVs in the U.S. (1963-1979)

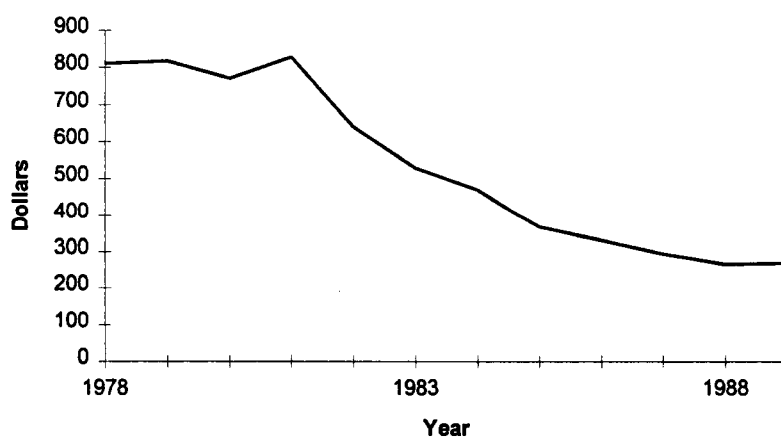


Figure 4.3 The Average Price of VCRs in the U.S. (1978-1989)

Table 4.1 Estimation Results for Color TVs

Model	R^2 /Adjusted R^2	Int.	U^{new}	$N / N^{1/2\sim}$	$N^2 / N\sim$
Basic Model	0.4544 / 0.3704	1.7075** (2.715)	n/a	0.1866* (3.290)	-0.0033* (-3.174)
The Proposed Model 1	0.7001 /0.6539	-1.3230 (-1.505)	n/a	2.5276* (5.383)	-0.2750* (-5.044)
The Proposed Model 2	0.8252 / 0.7815	-2.661* (-3.190)	0.00158** (2.932)	3.603* (6.887)	-0.4515* (-6.088)

1. $\sim$: Basic Model uses N and N^2 as independent variables while the Proposed Models use $N^{1/2}$ and N .
2. Values in parentheses are t-statistics.
3. * indicates the significance level at 0.01.
4. ** indicates the significance level at 0.05.

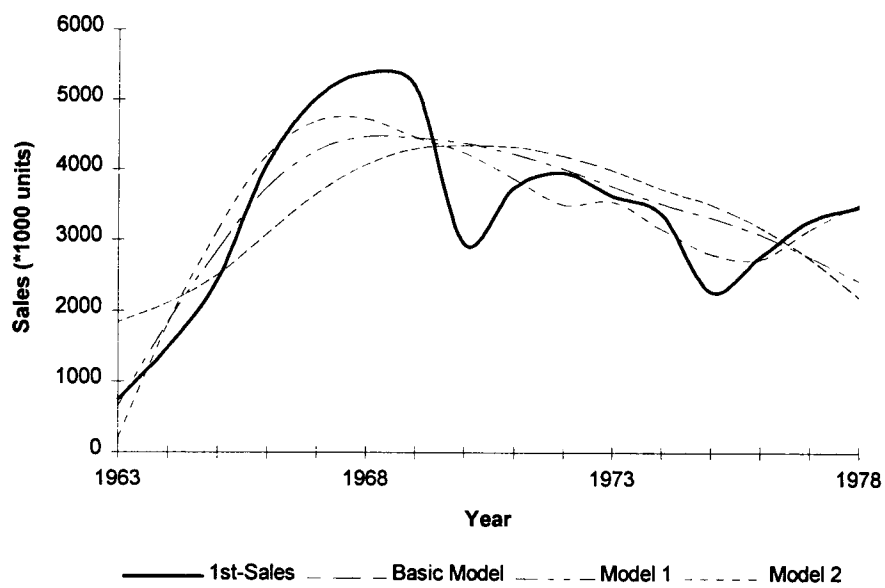


Figure 4.4 First-Purchase Sales of Color TVs in the U.S. (1963-1978) and Comparisons of Model Fitting

Table 4.2 Estimation Results for VCRs

Model	R^2 /Adjusted R^2	Int.	U^{new}	$N / N^{1/2} \sim$	$N^2 / N \sim$
Basic Model	0.9905 /0.9884	-0.02516* (-3.5368)	n/a	0.5424* (22.02)	-0.00549* (-15.801)
The Proposed Model 1	0.9387 /0.9251	-3.5368** (-3.069)	n/a	3.7673* (5.570)	-0.2421* (-3.277)
The Proposed Model 2	0.9772 /0.9687	-1.4944 (-1.608)	-0.000000466* (-3.679)	1.7280** (2.477)	0.11194 (1.042)

1. $\sim$: Basic Model uses N and N^2 as independent variables while the Proposed Models use $N^{1/2}$ and N .
2. Values in parentheses are t-statistics.
3. * indicates the significance level at 0.01.
4. ** indicates the significance level at 0.05.

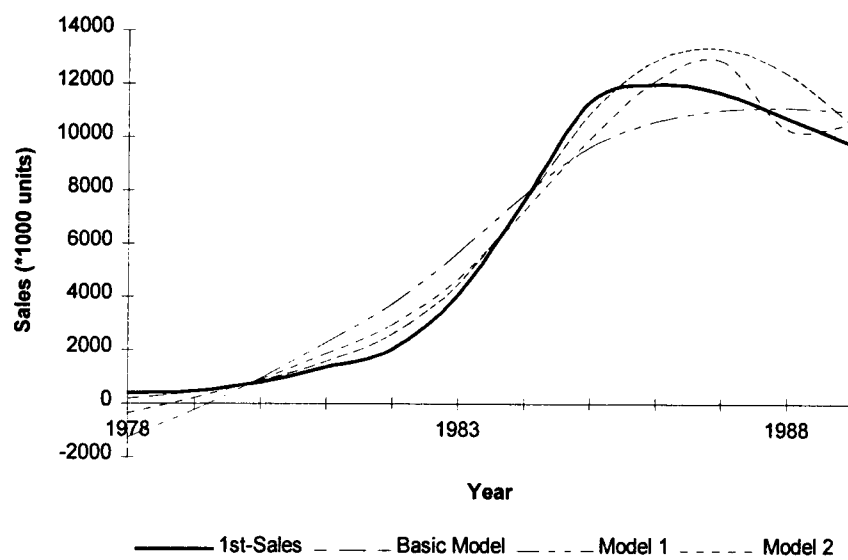


Figure 4.5 The Sales of VCRs in the U.S. (1978-1989) and Comparisons of Model Fitting

volume of sales and drops significantly after the peak due to its symmetric nature. On the contrary, the poor performance of the proposed models is largely due to the mismatching of sales at the initial stages of the sales curve of VCRs.

The Additional Contribution of U^{new} Term

The above study excludes the impact of U^{new} , another unique feature of the proposed model. After examined the performance of model 1, we now study that of model 2. The primary purpose is to evaluate the incremental impact of the U^{new} term on, or its additional contribution to, the performance of model 1. Since the U^{new} has been confined as a function of the income price ratio, maximum likelihood procedure is used to identify the power parameter of the Box-Cox transformation.

The maximum likelihood function for (4.1) can be written as

$$ML(\lambda) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2} - \frac{n}{2}\ln\tilde{\sigma}^2(\lambda) \quad (4.10)$$

where n is the sample size and $\tilde{\sigma}^2(\lambda)$ is the estimated error variance as a function of the parameter λ . A grid-search method is employed to identify the maximum likelihood estimate of λ .⁹ The optimal value of λ is found to be 3.05 for color TVs and 4.61 for

⁹ See Appendix B for the computing codes written in MATLAB that searches for the best LAMBDA value and perform the maximum likelihood estimation. The program has been written for an intended two-way search. It requires the input of the boundary for searching, as defined by the upper and lower limits for both LAMBDA1 and LAMBDA2. The output is an 11 by 6 matrix of calculated ML values as well as the highest ML value within this matrix. We can change the size of the searching area to

VCRs. The confidence intervals for the above estimates can be constructed because $2[ML(\tilde{\lambda}) - ML(\lambda)]$ is approximately a χ^2 distribution with one degree of freedom. For a 95% confidence interval, the confidence region consists of all values of λ that satisfy the inequality $ML(\tilde{\lambda}) - ML(\lambda) \leq \frac{1}{2} \chi_1^2(0.05)$. The examination of the confidence regions shows that the optimal functional form of income-price ratio in color TV study is not significantly different from a linear form, but is significantly different from a logarithm form; that the optimal functional form of income-price ratio in VCR study is significantly different from both linear and logarithm forms. More to the interest of this study, the significance tests with maximum likelihood values show that the equation including the U^{new} term is significantly different from the one without it.¹⁰

The inclusion of the U^{new} term in model 2 increases the model's explanatory power as demonstrated by the increased R^2 values in the cases of both color TVs and VCRs. In the validation study with color TVs, the parameter estimate for U^{new} is significant at the 5% level, and the rest of the parameter estimates are all significant at the 1% level. The model R^2 increases to 0.8252 from the 0.7001 of model 1. As can be seen from Figure 4.4, the fit of model 2 to the first-purchase sales data is much better than model 1. Model 2 seems to catch the variation of sales around the general trend of the

obtain the desired level of precision for LAMBDA. The program also generates model R-square and coefficient estimates with their variances for the maximum likelihood LAMBDA value.

¹⁰ For color TV study, the maximum ML value is $ML(3.05) = -12.0767$ while $ML(1) = -12.4726$, $ML(0) = -13.7741$ and $ML(\text{without the } U \text{ term}) = -16.3975$.

For VCR study, the maximum ML value is $ML(4.61) = -12.9365$ while $ML(1) = -18.7545$, $ML(0) = -18.2977$ and $ML(\text{without the } U \text{ term}) = -18.8770$.

market growth curve for color TVs. Of course, many other social and economic forces contribute to the variation of the curve. Including such forces in the model is expected to increase its performance.

In the validation study with VCR sales data, the inclusion of U^{new} term increases the R^2 value for the model 2. However, the parameter estimate for U^{new} yields a negative sign, which seems contrary to the general expectation, although its magnitude is very small. Besides, the parameter estimate for N becomes insignificant. Such problems may be attributed to the data contamination of its first-purchase sales and the lack of the series length. Figure 4.5 shows that model 2 provides a better fit to the sales curve. The funny turn-around at the sales peak seems to cause a problem for the sign of the parameter estimate of U^{new} term.

Econometric Properties

Econometric studies indicate that efficient estimation is achieved only when the underlying assumptions of an econometric/statistical model are satisfied (see Kmenta 1986). The most common problem for analysis with time series data is the autocorrelation. The Durbin-Watson test is therefore used to examine the existence of autocorrelation in the above models.

The Durbin-Watson's D value is found to be 0.828 for the basic model when studying color TVs, along with the correlation coefficient of 0.479. The null hypothesis that no autocorrelation exists can be rejected at the 5% significance level. In contrast, the

proposed models do not incur this problem. The Durbin-Watson's D values are 1.260 for model 1 with the correlation coefficient of 0.293, and 2.003 for model 2 with the correlation coefficient of -0.037. Both models do not exhibit significant autocorrelation problems. The use of Box-Cox transformation seems to have reduced the possible model misspecifications, an advantage asserted by Box and Cox (1964). The autocorrelation problem did not arise in the study with VCR data series.

The above results lead to such a conclusion: The proposed model provides a valid model specification. It provides a good description for market growth, as defined by the long-term first-purchase sales of a new product. The example is provided by the study of color TVs.

Summary

An empirical study is performed in this chapter to examine the validity of the specification for the proposed model. The $N^{1/2}$ and U^{new} terms are unique to the proposed model and have direct implications for the inference of consumer perceptual and behavioral parameters. Particular emphases are placed on the model performance with such two terms. The study also examines the impact of income and price on the market growth of new products through the consideration of the U^{new} term. The Box-Cox transformation and maximum likelihood methods are employed to determine the optimal functional form of the U^{new} term.

Empirical results with long-term first-purchase sales data of color TVs strongly support the validity of the specification of the proposed model. Every parameter estimate is significant, and the model R^2 increases substantially (from 0.4544 for the basic model to 0.7001 for model 1 and 0.8252 for model 2). The plot of model performance in Figures 4.4 and 4.5 provides the explanation for such improvement. The proposed model catches the general trend and explains to some extent the variations around the trend with the variation of income price ratio. The relatively poor performance of the proposed model regarding VCR sales seems attributable to data contamination of first-purchase sales and insufficient length of the data series.

Chapter 5

The Implication of the Model

One embarrassment for new product developers has been that a high rate of new product failures persists. To change this situation requires not only better management, but also more advanced quantitative techniques and knowledge. Quantitative knowledge helps to provide more precise descriptions of market growth behaviors of new products so that strategies can be employed and management can perform with greater confidence. This study has been a step toward this direction by providing an analytical framework to examine the diffusion of new products. This chapter discusses the model implication for improving the rate of success for new product development. It also briefly discusses the implication for economics study.

The Failures of New Products

New products are important to firms as well as to consumers. Presenting both opportunities and risks, new products are the sources of sales and profits for firms (see Urban and Hauser 1980). They change the existing markets, create new markets, and result in the dynamics of market competition and industrial evolution. As Schumpeter wrote about this world (1950): "The fundamental impulse that sets and keeps the

capitalist engine in motion comes from the new consumer's products, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates." As the pace of technological innovation speeds up and the product life cycles become shortened,¹¹ the need for rolling out new products more frequently and successfully exerts increasing pressures on firms. New product development is a serious issue because it is related directly to the survival or death of firms.

New products are equally important to consumers as well because they enhance the qualitative aspects of people's lives. As Rosenberg (1982, p. 4) wrote: "... to ignore product innovation and qualitative improvement is to ignore what may well have been the most important long-term contribution to ... human welfare."

New product development is a risky business because new products often fail. The statement has been made from time to time that as many as eight or nine out of ten new products turn out to be failures. Indeed, a U.S. Department of Commerce study supported this claim (see Crawford 1977). Depending on the criteria, the failure rates of new products range from 35% to 90%.¹² Kuczmarski & Associates studied the success

¹¹ Olshavsky (1980) empirically tested the shortening of product life cycles due to rapidly accelerating technological progress.

¹² See G. Gruenwald (1985), *New Product Development* and C. M. Crawford (1977), "Marketing Research and New Product Failure Rate," in *Journal of Marketing*.

The criteria for new product failure used in previous studies include failure to meet management expectation, low profit margin, abandoned product, and disappearance from store shelves within five years from the time of introduction. The failure rate also depends on the definition of a new product. The farther back along the development process to set the cut-off point for the definition of a new product, the greater it tends to be the rate of new product failure.

rate of 11,000 new products launched by 77 manufacturing, service and consumer-products companies. They found that only a little more than half (56%) of all products actually launched are still on the market five years later.¹³ One direct consequence of new product failure is the financial burden on firms. For example, the financial loss for Ford's Edsel was \$250 million; RCA's videodisc, \$500 million; and Dupont's corfam, \$100 million. The impact of new product failure is not limited only to firms. It also causes added burdens for consumers whose welfare may be reduced by such losses.

Raising the success rate of new products is "one of the few areas left with the greatest potential for improvement."¹⁴ In fact, it looks increasingly like one of the final frontiers for U.S. companies that spent the 1980s improving efficiency and boosting quality and that now are facing vicious competitive battles in slow-growth markets. As remarked by Yoram Wind, a marketing professor at the Wharton School, "If companies can improve their effectiveness at launching new products, they could double their bottom line." However, "when you look at failure rates for new products they have not changed much in 25 years," said William BonDurant, a top marketing executive at Hewlett-Packard Co.¹⁵

¹³ "Flops," cover story, *Business Week*, August 16, 1993, pp. 76-82.

¹⁴ Ibid.

¹⁵ Ibid.

Improving the Success Rate of New Product Development

The process of new product development probably covers all aspects of the business operations of a firm because a firm is “a synergy between different units at a given time to exploit economies of scale or scope” (Tirole 1990, p. 16) in providing products or services. However, the process can be roughly divided into two general phases, R&D and commercialization. The R&D phase includes new product concept evaluation, design, and testing and commercialization includes production, marketing, and logistics. Management, or skillful control, of these phases is necessary to ensure the success of new product development.

The knowledge of new product market growth is extremely important for the management of the new product development process in order to improve its success. Although other aspects of new product development are important, e.g., R&D/marketing interfaces, cross-functional teams, and so forth (see Souder 1988; Ruekert and Walker 1987; Song and Parry 1993), the advanced quantitative knowledge of the market growth behavior of new products seems to be the prerequisite. Better understanding of how much and how fast the market for a new product grows, i.e., the pattern of new product growth, can facilitate the development of strategies and business plans in a confident manner. A complete understanding of market growth behaviors of new products is critical for the success of new product development. Incorrect knowledge and forecasting of new product market growth can lead to the failure of new products. For example, William Barnett (1988) showed that optimism about the personal computer market resulted in the

overestimation of consumer demand. When firms finally realized it, most of them had to cut back production and some had to abandon their production altogether.¹⁶ Roberts and Urban (1988) indicated that knowledge of market growth behaviors is even more crucial for the success of high-priced consumer durables. Such consumer durable products usually do not go through traditional pre-market tests due to large initial production costs, thus making such knowledge more demanding.

This study is ventured to develop an alternative quantitative method to analyze the market growth behaviors of new products. A microapproach model of new product diffusion is proposed based on the latest knowledge of economics, marketing, and management sciences as well as psychology. By accounting for consumer behavioral and decision variables, it can serve as a fruitful analytical framework to evaluate the impact of individual behavioral and other decision variables on the patterns of new product diffusion. The future application of this model can be extensive. When all individual level measurements are well accomplished, the model can be used as a true pre-launch forecasting tool for the first-time sales of a new product. It can be applied at either product class level or brand level with consideration of product competition. The employment of product attribute theory as the analytical foundation in this study makes it

¹⁶ "In 1983 and 1984, 67 new types of business personal computers were introduced to the U.S. market, and most companies were expecting explosive growth. One industry forecasting service projected an installed base of 27 million units by 1988. Another predicted 28 million by 1987. In fact, only 15 million units had been shipped by 1986. By then, many manufactories had abandoned the PC market or gone out business altogether." — William F. Barnett, "Four Steps For Forecasting Demand," *Harvard Business Review*, Vol. 66 (1988), Iss. 4 (July/August), pp. 28-38.

possible to integrate the research on product design and positioning with that on innovation diffusion models.

However, the value of the proposed model should not be exaggerated. It is basically a new product diffusion model, i.e., a model methodologically appropriate for the market growth of the first-purchase sales of a new product. The proposed model considers primarily two important attributes in the new product diffusion, i.e., heterogeneity and uncertainty. Given the great complexity of the process of new product development, the effects of other factors should be also investigated. The mechanisms for repeat and replacement purchases need further exploration. Combined together, this information provides the advanced quantitative knowledge about the market behavior of new products. They can help assure better designed strategies and knowledgeable management for the success of new product development.

The Implications for Economics Study

The diffusion of technological innovations has long been an interest of economists. The diffusion process was attributed to the learning process by Mansfield (1968). Such attribution emphasizes only one aspect of the diffusion process. Based on the theoretical underpinnings from economics, as well as other disciplines, this study has provided a more comprehensive analytical framework to study the diffusion of an innovation in a heterogeneous population.

An innovation diffuses over time because its newness imposes both benefits and uncertainty to potential users so that the heterogeneity among users makes inevitable the

occurrence of the diffusion phenomenon. This study considers the heterogeneity, uncertainty reduction and individuals' perception about the innovation into a consistent framework. The biggest contribution is probably the use of product attribute as the analytical foundation. The construction of a multiattribute space provides a clear description and visualization of the progress of the diffusion process. The attribute approach is rich in contents and implications and explicitly considers the effect of individuals' differences or population heterogeneity on a multidimensional scale. Such an attribute approach can be theoretically more rigid than the traditional approach of statistical inference. It provides more insights into the impact of individual decision behaviors on the diffusion of new technologies. With such knowledge, we can forecast the diffusion of yet another new technology.

Chapter 6

Conclusion and Discussion

Conclusion

Summary of the Modeling Approach

This study has proposed an alternative micro approach model of new product diffusion for comprehending the market growth behaviors of new products. The scenario of this study is positioned as the diffusion of a new product in a heterogeneous population. Product attribute theory is used to construct a multidimensional space in which the preference heterogeneity of consumers, their choice behaviors and the consequent diffusion of a new product are analyzed. A descriptive approach to the decision behavior under uncertainty is adopted in light of the violations to the normative approach and the parsimony for the model development.

With the product attribute perspective, consumers are regarded as being distributed in a multiattribute space, reflecting their heterogeneous preferences and financial constraints. A new product is introduced with a certain combination of attributes and occupies a point in the space. Thus, individual consumers will behave differently to the new product because the distances between the location of the product and their ideal points are different. Shocker and Srinivansan's Euclidean Distance method is used to

model an individual's utility loss due to the existence of such distance. Uncertainty reduction is modeled through the consideration of size and dynamic effects, based on the descriptive approach. The dynamic effect introduces a dynamic dimension so that the progress of the diffusion process can be explained by consumer behavior parameters rather than by some exogenous factors as commonly assumed in previous micro approach models. The model further takes into account the perceived relative benefits of the new product, as represented by U^{new} , to construct a compensatory decision rule for an individual's adoption behavior. The analysis indicates an orderly pattern in the process of new product diffusion, which is named the *Diffusion Frontier*. The integration of those individuals within the frontier yields the total number of adopters. The integration of individuals' decision behaviors results in a differential equation for the diffusion of a new product, whose parameters are determined by consumer perceptual, behavioral, and decision variables. The equation is very similar to that of the Bass model except the meaning of model parameters and the specification of the model variables.

Conclusions

The model developed in this study provides an analytical framework for the diffusion of innovations. The inclusion of decision and consumer behavior variables is based upon rigid theoretical and empirical supports. The model is relatively comprehensive and consistent rather than a "piecemeal" type of improvement. A simulation study is performed to illustrate the impact of individual level variables on the

diffusion of a new product. The simulation shows that the perceived relative benefits of a new product affect only the sales growth when a certain condition is not met and that they affect both the sales growth and the market potential when the condition is met. It also shows that reduced product salience does not affect the speed of new product diffusion but increases the volume of its market potential. The size and dynamic effects, measures of the consumer behavioral characteristics under uncertainty, affect the new product diffusion patterns significantly. The size effect influences the market potential, and the dynamic effect influences the rate of diffusion or market growth of a new product.

Empirical validation with the long-term first-purchase sales of color TVs has been very positive in supporting the proposed model specification. The consideration of consumer income and new product price is made through the U^{new} term of the perceived relative benefits of the product. All model parameter estimates are statistically significant and model R^2 increases significantly over the basic model, an equivalent model to the Bass model of new product diffusion. The validation study with the VCR data has not been as good. The primary reason for that is the data contamination and insufficient length of the data series for VCRs.

Discussion

Contributions

The primary contribution of this study is the proposal of a consistent and relatively comprehensive model of new product diffusion. The contributions can be discussed from both theoretical and empirical perspectives.

1. From the theoretical perspective, this study uses the product attribute theory to construct an analytical framework with which to study the market growth behaviors of new products. It materializes the conceptual framework theorized in the general study of the diffusion of innovations into an operable framework for quantitative analysis. Such a framework helps visualizing the process of new product diffusion through the derivation of the diffusion frontier. This approach has extensive literature support and a great potential to integrate the research on innovation diffusion models with that on product design and evaluation as well as consumer measurements.

2. It adopts a descriptive approach to decision behavior under uncertainty to develop a parsimonious model. In particular, it uses the size effect to capture individuals' learning and imitating behaviors; It employs the dynamic effect to capture the impact of event volatility on individuals' decision behaviors. The benefits of taking the descriptive approach are much more than just the development of a parsimonious model. It is an attempt to accommodate real consumer behaviors in the scenario of new product diffusion, where violations to the normative theory are widely observed due to the persistent uncertainties involved.

3. As a theoretical model, this study provides valuable propositions for constructing testable hypotheses. The results from simulation study provides some such examples. We can gain more understanding of the diffusion of innovations by verifying or disproving such hypotheses.

4. From the empirical perspective, this study is the first to employ Box-Cox transformation method for the model estimation. This method suits perfectly the need of model estimation when model variables have unknown functional forms.

5. It incorporates new product price and consumer income in a different way. The model considers them, in the form of income price ratio in this study, as the primary deciding variable for the perceived relative benefits of a new product. Empirical validation with such model specification has produced positive results.

Limitations

Since this study is primarily a theoretical model development, it involves assumptions and simplifications thus the limitations.

1. From the theoretical perspective, this study investigates only two major factors for the diffusion of new products, i.e., consumer preference heterogeneity and the effect of uncertainty reduction. The analytical nature of the model involves assumptions concerning consumer distributions in the product attribute space. The model is deterministic by its expression. Therefore, it is limited in terms of the consideration of other factors that may influence new product diffusion. Some possible extensions are

discussed at the end of Chapter 3. To overcome such limitation, however, requires much more than a brief discussion.

2. From the empirical perspective, this study contains only a limited validation study. As stated before, a more powerful and extensive study should be a full-scale application of the model that involves the survey and estimation of consumer behavioral parameters and that of products as well. The model developed through such an approach possess as the potential for pre-launch forecasting of new product diffusion. Yet much work remains to be done.

Potential Uses of the Model

As discussed in Chapters 1 and 5, this study is motivated by the understanding that the improvement of advanced quantitative knowledge about market growth behaviors of new products can help ensure more successful new products. By linking product life cycle with strategic planning practice, innovation diffusion models have served as analytical tools to provide such knowledge. For the past three decades, researchers have been improving traditional models to make them more relevant for managerial purposes. This study takes the micro approach to comprehend the mechanism and process of new product diffusion through the analysis of individual decision behaviors.

Most of the problems associated with previous innovation diffusion models can be explained with the proposed model. The model does not assume any restricted market boundaries. The market potential is determined by a set of consumer behavioral variables.

Strategic variables affect the market potential of new products through their influences on individual consumers. The knowledge on individual consumers' behaviors yields the understanding of new product diffusion. Perceived relative benefits of a new product are captured by the model variable U^{new} . The changes in consumer income, new product price, functions, and so on can affect its value and consequently the diffusion of the new product. Of which, the effects due to income and price have been investigated in this study. The notion of consumer distributions in a product attribute space introduces the possibility to study the phases of consumer decision behaviors. At least one additional phase can be added for the analysis within the model, i.e., consumer awareness besides the traditional binary adopt/not-to-adopt decisions. Such awareness is captured by the effective density of consumer distribution in the space.

As such, the proposed model serves the basic functions of innovation diffusion models. In addition, the author foresees the following potential and beneficial uses of the model:

1. Pre-launch forecasting of new products. The most challenging and rewarding task, forecasting the market growth of new products is one basic function of new product diffusion models. The proposed model offers the advantage that model parameters can be obtained through the analysis of consumer responses toward early products plus the adjustment of the current changes of consumer behaviors. It demonstrates a meaningful way to perform pre-launch forecasting tasks.

2. Evaluation of new product improvement. Survey results of consumer responses to new product improvement, such as the addition of new features, functions and so on, can be used to evaluate the actual market growth curves. The evaluation can be used to assess the cost effectiveness of alternative improvements on new products.

3. Analysis of new product diffusion under competitive pressures. Competition changes consumers' valuation regarding the current product. Therefore, the distribution of U^{new} is expected to be altered. Such altered U^{new} distributions in an attribute space will affect the diffusion of new products. The analysis from this perspective can gain insights into the influence of competition on the diffusion of new products.

4. An integrated computer model to perform forecasting and market analysis. Because the model analysis is in a product attribute space, new product diffusion becomes an intuitive and visualized process. A computer model can be developed, based on this framework, to track, provide feedback, and analyze the diffusion process or market growth behaviors of a new product.

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APPENDICES

Appendices

A. The Derivation of Ellipse Diffusion Frontier

We begin with the equation (3.12),

$$-U^{new} = -\sum_{k=1}^m \alpha_k (A_{ik}^* - A_k)^2 + \beta \sqrt{N} - \gamma \frac{dN}{dt}. \quad (a1-1)$$

At a given moment during a diffusion process, U^{new} , N^2 and dN/dt are of certain values and the trajectory of A_{ik}^* defines a frontier where marginal individuals are adopting the new product.

By putting U^{new} , $\beta \sqrt{N}$ and $\gamma * dN/dt$ together and denoting them by a new term C^2 , $C^2 = (U^{new} + \beta \sqrt{N} - \gamma \frac{dN}{dt})|_{t=t}$, we can write (a1-1) as simple as,

$$\sum_k \alpha_k (A_{ik}^* - A_k)^2 = C^2 \quad (a1-2)$$

and for a two-dimensional case,

$$\alpha_1 (A_{i1}^* - A_1)^2 + \alpha_2 (A_{i2}^* - A_2)^2 = C^2. \quad (a1-3)$$

Ignoring the index for individuals and considering that A_1 and A_2 are actually the attribute levels provided by the new product, we rewrite (a1-3) to make it consistent with Figure 3.1,

$$\alpha_1 (A_1 - A_{10})^2 + \alpha_2 (A_2 - A_{20})^2 = C^2. \quad (a1-4)$$

(a1-4) is a typical ellipse equation in geometry. The solution is an ellipse that centers at (A_{10}, A_{20}) and has the ratio of the radius along the attribute 1 axis over the radius along the attribute 2 axis at $\sqrt{\alpha_2/\alpha_1}$. As the C^2 increases over time, a family of concentric ellipses can be obtained, representing the expansion of the diffusion frontier of a new product.

B. Computing Codes in MATLAB : for the maximum likelihood estimation and the determination of Box-Cox transformation parameter

```
% This program is for my Ph.D. dissertation research.
% It performs the Box-Cox estimation procedure for: Color TV
% via a 2-way grid search for the maximum ML value.
% Last revision @ 02/09/95

clear
%diary ctv.out
% INPUT DATA for === colortv ===
% data format: year sales income/price
load colortv.txt
% define variables y=sales
% x1= I/P to be transformed
% x2= any variable to be transformed
y=colortv(:, 3);
x11=colortv(:, 5);
x12=colortv(:, 6);
x1=x11./x12;
[n, p]=size(y);
x2=colortv(:, 4);
x3=x2^0.5;
% to construct constant term
ONE=ones(n,1);
%disp('')
%disp('Note: the intervals for ***** LAMBDA1 : 10 & LAMBDA2 : 5 *****')
up1=input('The upper limit for LAMBDA1: ');
low1=input('The lower limit for LAMBDA1: ');
up2=input('The upper limit for LAMBDA2: ');
low2=input('The lower limit for LAMBDA2: ');
pace1=(up1-low1)/10;
pace2=(up2-low2)/5;
%set initial values
% out(ml, mlmax, R2, BETA(q), VARIANCE_BETA(q))
out(2)=-99999;
for i2=1:6
    x2bc=[];
    index2(i2)=low2+pace2*(i2-1);
    for i=1:n
        if index2(i2)==0
            x2bc(i)=log(x2(i));
        else
            x2bc(i)=(x2(i)^index2(i2)-1)/index2(i2);
        end
    end
    x2bc=x2bc';
    for i1=1:11
        x1bc=[];
        index1(i1)=low1+pace1*(i1-1);
        for i=1:n
            if index1(i1)==0
```

```

        x1bc(i)=log(x1(i));
    else
        x1bc(i)=(x1(i)^index1(i1)-1)/index1(i1);
    end
end
x1bc=x1bc';
X=[ONE x1bc x2bc x3];
[n,q]=size(X);
out=logml(y, X, out);
ML(i2,i1)=out(1);
end
end
ML=ML';
column=index1';
result=[0, index2; column, ML]
mlmax_R2=[out(2), out(3)]
beta_variance_tvalue=[out(4:3+q); out(4+q:3+2*q); out(4:3+q)./out(4+q:3+2*q)]
contour(ML)
%pause
%mesh(ML)
diary off
end

```

```

function out=logml(y, X, out)
% This is the subroutine to calculate and output the log-ML values
%                                     and update 'out'.
%   logml   :   output, 1 by 1 scalar
%   out     :   output/input vector
%   y       :   input, nn by 1 vector ==== sales
%   X       :   input, nn by k matrix
%
%               For a given input set, the subroutine outputs a scalar
%               and
%               updates   R_2, b, var
[nn,q]=size(X);
beta=inv(X'*X)*X'*y;
sigmasqhat=(y-X*beta)'*(y-X*beta)/nn;
varhat=sigmasqhat*nn/(nn-q);
logmlvalue=-nn/2*log(2*pi)-nn/2-nn/2*log(sigmasqhat);
out(1)=logmlvalue;
if logmlvalue > out(2)
    out(2)=logmlvalue;
    yprime=y-mean(y);
    out(3)=1-sigmasqhat*nn/(yprime'*yprime);
    out(4:3+q)=beta';
    covbeta=varhat*inv(X'*X);
    sebeta=covbeta.^0.5;
    out(4+q:3+2*q)=(diag(sebeta))';
end
return

```

Vita

Sha, Zheng-Ming (Richard), was born in Nanjing on November 26, 1962. Most of his childhood was spent with his grandparents in the City of Changsu, Jiangsu Province, where he finished the junior school. He then moved to live with his parents and entered high school there.

He was fortunate to stand out by winning the championship of math and physics contests in the region. As a result, he was permitted to take entrance examinations for the universities two years before the scheduled graduation. He passed that with high scores to enter Nanjing University to study Physics in September 1978. He graduated from the University in July 1982 and pursued his graduate study in Information Physics in joint with the Acoustics Institute of Nanjing University. He got to know Wendy, now his wife, during the study.

After obtained the M.S. degree, he moved to Shanghai to assume a faculty position in Shanghai JiaoTong University in August 1985, first at the administration headquarters and then the Management School. Starting January 1988, he worked with the Shanghai Branch of International Technology and Economy Institute, where he researched on a variety of issues including comparative technological development and management.

He entered the graduate program of Economics at the College of Business Administration, The University of Tennessee, Knoxville in January 1990. His main interest has been in quantitative methods and the management of new products and new technologies. He expects to graduate with a Ph.D. degree in August 1995.