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*A Study on Multilevel
Substitution Models of Innovation Diffusion:
A New Approach of Modelling*

By

Jian Guo, M.A.

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of
the requirement for the degree of

Master of Management Studies

School of Business
Carleton University
Ottawa, Canada

December, 1997

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and Research acceptance of the thesis

A Study on Multilevel
Substitution Models of Innovation Diffusion:
A New Approach of Modelling

submitted by Jian Guo, M.A.
in partial fulfilment of the requirement for
the degree of Master of Management Studies

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Abstract

One of the major tasks of the modern firms is the development of new products. Forecasting the sales of these new products is of critical importance to firms. Diffusion models make forecasts or present a description of the diffusion process but few of these models deal with the multilevel substitution phenomenon. This thesis focuses on developing a new approach to estimating the parameters of diffusion models for describing multilevel substitution and comparing the predictive ability of selected models with that of a new one. Two sets of sales data, Dynamic Random Access Memory (DRAM) and Tire Cord fabric, have been selected for testing.

The findings of this study suggest that (1) new models built by new approach have better predictive ability than other selected models, (2) the internal influence of diffusion process decreases and external influence of diffusion process increases over product generations.

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Chapter 1

Introduction

The development of new products and processes is increasingly a focal point of competition. Firms that can get to market faster with products that are well matched to the needs and expectations of target customers do better. Firms that are slower to market with products that match neither customer expectations nor the products of their rivals are destined to see their market position erode and financial performance falter (Clark and Wheelwright 1993 p.3).

Clark and Wheelwright (1993) claimed that new products were central to the growth and prosperity of modern corporations. New-product programs were reported to be plagued by high failure rates and disappointing results (Cooper 1987). Competition at home and abroad, the internationalization of markets, and the quickening pace of technological change were forcing companies to make product innovation a vital facet of corporate plans (Cooper and Kleinschmidt 1991).

Cooper and Kleinschmidt (1991 p.5) stated that companies were becoming increasingly dependent on new products. In 1986, for example, approximately 40% of sales of US firms came from new products - up considerably from 33% five years earlier. Cooper (1987) pointed out that new products that got to the marketplace face a failure rate of somewhere between 35 and 50 percent.

Olshavsky (1980) stated that, parallel to these high failure rates, there was some indication that the rate of adoption of new products was increasing, while the product life cycle was shortening. Forecasting via diffusion models, the potential outcomes such as sales, profit and market share has been proposed as a useful technique to describe and predict the development of sales for a new product.

Researchers in management and marketing science have contributed to the development of diffusion theory by suggesting analytical models for describing and forecasting the diffusion of an innovation in a social system (Mahajan, Muller and Bass, 1990). Mahajan and Muller (1979) pointed out that the objective of a diffusion model was to present the level of spread of an innovation, among a given set of prospective adopters, over time. The purpose of the diffusion model is to depict the successive increases in the number of adopters and predict the continued development of a diffusion process already in progress (Mahajan, Muller and Bass, 1990).

Manufacturers of high technology products usually achieve diffusion in the marketplace by offering successive generations of an innovation. Each generation is positioned to be "better" than its predecessors on relevant product attributes. Assessment of market penetration, therefore, is critical for successive generations of a high technology product. In addition to creating its own demand, each generation of the product cannibalizes the diffusion of its predecessors (Mahajan, Muller and Bass, 1990). But, in fact, such cannibalization may vary greatly in extent over a number of products.

Many different models have attempted to make accurate forecasts or descriptions of the diffusion process but few dealt with the multilevel substitution phenomenon. This research focuses on developing a new approach to estimate the parameters of diffusion models for describing multilevel substitution processes. Dynamic Random Access Memory (DRAM) integrated circuits (IC) and tire cord (TC) fabric sales data were selected as testing data sets. Testing included two contexts: how well these selected models can describe the sales pattern of each generation product and how well the models forecast future sales.

The remainder of this thesis was divided into six Chapters. Chapter two is a review of the pertinent literature, in which, the theory of the diffusion process, three types of diffusion models and selected multilevel models were discussed. Chapter three states the research problems and objectives. Chapter four outlines the methodology. Chapter five reports the findings of study. Chapter six concludes this study by summarising the research presented and Chapter seven presents the limitations of the research and suggestions for future research.

Chapter 2

Literature Review

2.1 The Diffusion Process

The diffusion of an innovation is defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers 1983 p.5). Clearly, this definition includes the four basic elements of the diffusion process: (1) innovation (2) communication channels (3) time, and (4) the social system. Each of these elements was considered in turn.

2.1.1 The Innovation

Innovation resulting in a major product change is a complicated activity which begins with the recognition of a problem and the conception of an idea as a possible solution to that problem. It continues through the actual utilization of the idea in the solution of the problem, and finally the adoption of that idea as the predominant mode of solution to that problem (Lundstedt and Colglazier, 1982) may occur. Once the prototype product is released to the market, usually during the pilot phase of manufacture, the diffusion process begins. Diffusion of innovations is the means by which an innovation is spread throughout an industry and thus replaces an older technology (Lundstedt and Colglazier, 1982). Consequently, diffusion is a part of the innovation process. The diffusion process is

extremely important because this is when decisions made early on in the innovation process are determined to be correct or not. Rogers (1983) defined an innovation as an idea, practice, or object that was perceived as new by an individual or other unit of adoption. Three types of innovations have been outlined by Robertson (1971). They are continuous innovation, dynamically continuous innovation, and discontinuous innovation.

A continuous innovation represents a small disruption of behavioural patterns and depicts the modification of an existing product or process. A dynamically continuous innovation represents some disruption in behavioural patterns rather than changing them considerably. It may include the creation of a new product or the modification of an existing product. A discontinuous innovation includes development of a new product and involves some disruption of existing behavioural patterns. According to these definitions, new DRAM products and tire cord fabric fall in the continuous innovation category since new generation products have the same behavioural patterns as older generations.

The research by Rogers (1983) on the diffusion of innovations identified many consumer characteristics which typically differed between early and late adopters. This means there are some consumer characteristics which result in a tendency to adopt early or late. There are a number of factors affect the value or utility the consumer places in the product. The perceived functional and performance characteristics of the product in relation to the consumers lifestyle, age and social status are important here. The reliability and durability of the product may be considered by the consumer also. The perceived uncertainty

associated with imperfect information, together with the consumer's risk aversion, have also been shown to contribute to the decision.

Different products have different rates of adoption. Rogers (1983) contended that characteristics of innovation, as perceived by individuals, helped to explain their different adoption rates. He defined five attributes of innovations as follow: (1) Relative Advantage, (2) Compatibility, (3) Complexity, (4) Trialability, and (5) Observability.

(1) **Relative Advantage** is the degree to which an innovation is perceived as better than the idea it supersedes. The greater the perceived relative advantage of an innovation, the more rapid its rate of adoption is going to be.

(2) **Compatibility** is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters.

(3) **Complexity** is the degree to which an innovation is perceived as difficult to understand and use. Some innovations are readily understood by most members of a social system; others are more complicated and will be adopted more slowly.

(4) **Trialability** is the degree to which an innovation may be experimented with on a limited basis. New ideas that can be tried on the "instalment plan" will generally be adopted more quickly than innovations that are not divisible.

(5) **Observability** is the degree to which the results of an innovation are visible to others. The easier it is for individuals to see the results of an innovation, the more likely they are to adopt. Such visibility stimulates peer discussion of a new idea as friends and neighbours of an adopter ask him or her for innovation-evaluation information about it.

In general, innovations that are perceived as having greater relative advantage, compatibility, trialability, observability and low complexity will be adopted more rapidly. These are not the only qualities that affect adoption rates, but past research indicates that they are the most important characteristics of innovations in explaining adoption.

2.1.2 Communication Channels

Communication channels are the methods by which information is shared by consumers and marketing organizations. How quickly a product innovation spreads through a market depends, to a great extent, on communication between the members of a social system. Engel, Blackwell, and Miniard (1990) defined communication as the "process by which consumers and marketing organizations shared information with one another to reach mutual understanding". The central concern of marketing researchers has been the influence of both mass media channels of communication (i.e. advertising) and interpersonal channels of communication. Rogers (1983) noted that the essence of the diffusion process was the information exchanged by which one individual communicated a new idea to one or several others. In its most elementary form, the process involves: (1) an innovation, (2) an individual

or other unit of adoption that has knowledge of, or experience with using it, (3) another individual or other unit that does not yet have knowledge of the innovation, and (4) a communication channel connecting the two units. A communication channel is the means by which messages pass from one individual to another. Rogers (1983 p.18) also pointed out that dependence on the communicated experience of near-peers was at the heart of the diffusion process and was modelled and imitated by potential adopters of their network partners who had adopted previously.

2.1.3 Time

Time is an important element in the diffusion process. Time is also an obvious aspect of any communication process, but most (nondiffusion) communication research does not deal with it explicitly. Perhaps it is a concept that cannot be explained in terms of something more fundamental (Whitrow, 1980, p.372). Time does not exist independently of events, but it is an aspect of every activity. Adoption of a new product is considered to be a process over time. Engel, Blackwell, and Miniard (1990) noted that consumers decided to purchase products in varying amounts of time and usually passed through a multistage process. Rogers (1983) and many others considered the decision process as the stages of knowledge, persuasion, decision, implementation and confirmation.

The inclusion of time as a variable in diffusion research is critical, but the measurement of the time dimension (often by means of respondent recall) is open to

criticism. The time dimension is found: (1) in the innovation-decision process by which an individual passes from first knowledge of an innovation through its adoption or rejection, (2) in the innovativeness of an individual or other unit of adoption--that is, the relative earliness/lateness with which an innovation is adopted--compared with other members of a system, and (3) in the innovation's rate of adoption in a system, usually measured as the number of members of the system that adopt the innovation in a given time period. Clearly, adoption of a new product is not immediate, it takes time with various stage of decision process.

2.1.4 The Social System

Rogers (1962) suggested the concept of adopter categories involved the determination of a classification scheme that indicated where a consumer stands in relation to other consumers in terms of his or her adoption of a new product. According to Rogers (1962), the initial 2.5 percent of adopters (innovators) are willing to accept risk. The next 13.5 percent are early adopters who are considered role models. The next group of 34 percent are called the early majority and consider innovation only after peers have adopted. The next group, which accounts for the next 34 percent, needs overwhelming pressure from peers before they adopt. The final 16 percent of adopters are laggards. In the past few decades, this model has become widely used as a research basis. A weak point of this model is that "nonadopters" are not included, since the assumption is that 100 percent of the members of a social system under study will eventually accept the product innovation. However, Rogers's model

provides a research basis of different adopter classes.

2.2 Diffusion and Substitution Analysis

Analysis of historical data from a considerable number of phenomena shows that cumulative sales often follow a regular pattern (e.g. S-shaped curve) when cumulative sales are plotted against time.

Analysis of a great many cases supports the general premise that diffusion is a result of both a smooth evolution in time combined with random factors. If the cumulative adoption time path or temporal pattern of a diffusion process is plotted, the resulting distribution can generally be described as taking the form of an S-shaped (sigmoid) curve (Mahajan and Peterson, 1985). The term "S-Shaped Curve" represents a loose analogy between the growth in performance of a new product and the growth of a living organism. It is descriptive and evokes an image of a pattern of new-product change. Figure 2-1 shows an example of an S-Shaped Curve. The growth rates (dF/dt), in which dF is the proportion of potential adopters who have adopted an innovation up until time t , is slow at the initial stage and what follows is rapid exponential growth. However, sales growth slows as performance approaches a natural physical limit asymptotically ($F \rightarrow M$ as $t \rightarrow \infty$). It should be noted that different products have different growth rates (dF/dt). The upper limit is usually the result of market saturation. An approaching physical limit does not remove the need to forecast. For it is at such a time that a new product may emerge. This new product will have a different physical limit and a potential for further progress in performance. Figure 2-2 and

**Analytical Structure of S-Shaped
Model (Cumulative Adoptions)**

Figure 2-1

Figure 2-2

Figure 2-3

2-3 show the world-wide shipments of generations of DRAMs and tire cord products (Merino, D.N., 1990). Throughout this thesis, one assumption is made to simplify the analysis of data. This is to assume shipments equal to sales (Norton and Bass, 1987). The patterns of DRAM and tire cord cumulative sales are exactly S-Shaped Curve (Figure 2-4 and 2-5). This fact determined that this study would employ the diffusion and substitution models which deal with S-Shaped Curves.

Substitution analysis is concerned with tracking the replacement of one product by another when both the old and new products are designed to perform the same function. The relevant parameter is the fraction of the use captured by the new product.

Diffusion and substitution are different concepts. Diffusion is concerned with the rate at which a new product spreads and approaches its saturation limit. Substitution is concerned with the rate at which one product replaces another. However, substitution models are very similar to the basic diffusion models which are discussed in Section 2.3 except the unit of analysis is market share rather than sales or sales.

A complete substitution for the existing technology might be done over a period of time. This almost invariably occurs in process innovations where eventually the old technology disappears completely except, perhaps, for a very small residual amount. Sharif and Kabir (1976b) pointed out that many substitutions occur simultaneously. According to Norton and Bass (1987), new technology provides an opportunity for buyers of earlier

Figure 2-4

Figure 2-5

technologies to substitute the more recent technology. They also suggested that when the time interval between technologies is short, the earlier technology might continue to diffuse through a population of potential buyers even as the substitution process was underway. Therefore, the demand for an earlier technology may continue to grow even as the substitution process occurs.

Norton and Bass (1987) stated that most substitution models are market share models. Indeed, a principal distinction between substitution and diffusion models is that models of technological substitution assume there is a product available to be substituted and the size of demand for that product is known. In general, diffusion models make no such assumptions.

2.3 The Diffusion Models

Much of the early research on diffusion processes focused on describing observed diffusion patterns in terms of prespecified trends or distribution functions. For example, cumulative normal, Gompertz, and logistic distribution functions (Haines, 1964) have all been used to model diffusion processes because each gives rise to an S-shaped curve. In particular, diffusion models have been developed to represent the level or spread of an innovation among a given set of prospective adopters in a social system in terms of a simple mathematical function of the time that has elapsed from the introduction of the innovation. One purpose of a diffusion model is to depict the successive increases in the number of

adopters or adopting units over time (Mahajan and Peterson, 1985). Three types of diffusion model discussed are external, internal and mixed influence models.

2.3.1 External Influence Model

The assumptions of external influence models are: (1) the diffusion process is only influenced by sources outside of the social system such as mass media, activities of government agencies, interest groups and sales people, (2) interpersonal communication, for instance, word of mouth, is not considered to have any effect on the diffusion process.

$$\frac{dF(t)}{dt} = p [M - F(t)] \quad (2.1)$$

The external influence diffusion model can be expressed as follow:

Where

$F(t)$ = the fraction of the market that has been penetrated by time t .

p = a parameter, describing the effect of the external sources, is called the coefficient of innovation.

M = upper limit of the diffusion.

If there is a 100 percent diffusion of the new product, then $M=1$.

$dF(t)/dt$ = rate of diffusion during period 0 to t .

This thesis will use the above terminology throughout.

Much of the popularity of the external-influence model is due to the work of Coleman

et al.(1966), who used it to investigate the diffusion of a new drug by physicians in four Midwestern communities in the US

2.3.2 Internal Influence Models

The internal influence models considers interpersonal communication only between adopters and potential adopters instead of external influences such as mass media.

These models have the form

$$\frac{dF(t)}{dt} = q F(t) [M - F(t)] \quad (2.2)$$

where

$dF(t)/dt$ = rate of diffusion during period 0 to t.

$F(t)$ = the fraction of the market that has been penetrated by time t.

M = upper limit of the diffusion

q = a parameter which has the effect of interpersonal communication on adoption, is called the coefficient of imitation.

The rate of diffusion is the relative speed with which an innovation is spread to members of a population. The Fisher and Pry (1971) model, an internal influence model, is well known, and widely used, for technological substitution. It can be used to predict the future market share of two competing technologies. This model is based on three assumptions: (1) Many technological advances can be considered as competitive

substitutions of one method of satisfying a need for another. (2) If a substitution has progressed as far as a few percent, it will proceed to completion. (3) The fractional rate of substitution of new for old is proportional to the remaining amount of the old left to be substituted. The model is given by the following equation:

$$\frac{dF}{dt} = qF [1 - F] \quad (2.3)$$

where F is the fractional market share of the innovation of time t , and q is a constant of proportionality.

Solving equation (2.3), we can obtain the following expression.

$$F = \frac{1}{1 + e^{-qt}} \quad (2.4)$$

This equation is a logistic function.

The Fisher and Pry model "has been shown to fit the data well for a number of successive innovations " (Norton and Bass, 1987). The Gompertz model is a related internal influence model. It has the following form

$$\frac{dF}{dt} = qF \ln\left(\frac{1}{F}\right) \quad (2.5)$$

The solution of this equation (see Appendix E) is

$$F = e^{(-e^{-(e^{-qt})})} \quad (2.6)$$

2.3.3 The Mixed Influence Model

The mixed influence model can be expressed by the following equation

$$\frac{dF(t)}{dt} = [p + q F(t)] [1 - F(t)] \quad (2.7)$$

The mixed influence model considers both the effect of internal and external influence, as it indicates an additive association of the exponential and logistic models. The Bass Model (1969) is a well known mixed influence diffusion model and has been widely used for prediction purposes [Never (1972); Dodson and Muller (1978); Bass, Krishnan and Jain (1994)]. Bass proposed the model, where

p = the coefficient of innovation

q = the coefficient of imitation

Bass (1969) assumes that potential adopters are influenced by two channels: mass media and word of mouth. The Bass model's point of inflection can occur from 0 to 0.5 penetration and the diffusion pattern is nonsymmetric.

The solution of (2.7) is

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \quad (2.8)$$

$F(t)$ is the cumulative function and when $t=0$, $F(0)=0$.

It has been found that the Bass Model describes the empirical adoption curve well over a large number of new products and technological innovations. The effect of innovation

will be greater at an initial stage, while the effect of imitation will increase over time. Kalish and Lilien (1986) stated that empirical testing of the model revealed very good results initially, but subsequent research indicated that the model consistently under predicts sales as well as the peak time of sales. The Bass model focuses on external influence in the beginning of the diffusion process, while the effect of internal influence will rise over time. Actually, the Bass Model develops a "generalized logistic curve" (Mahajan and Peterson, 1985).

Russell (1980) and other economists have suggested that the Bass Model is incomplete because it did not combine contagion effects with traditional economic variables such as price (Bass, Krishnan and Jain, 1994). Since then, marketing researchers have developed models which include promotion, price and advertising variables. For example, Bass, Krishnan and Jain (1994) have generalized the Bass Model to include decision variables such as price and advertising.

The model's form is

$$\frac{f(t)}{1 - F(t)} = [p + qF(t)] X(t) \quad (2.9)$$

Where $X(t)$ is called "current marketing effect" to reflect the current effect of dynamic marketing variables on the conditional probability of adoption at time t . Bass, Krishnan and Jain (1994) stated that when $X(t)$ is constant, the Generalized Bass Model (GBM) would be observationally equivalent to the Bass Model. Thus, the Bass Model provides good fit to adoption data, while the GBM provides the same fit if $X(t)$ is constant.

The following table gives the characteristics of the models discussed above.

Model	Model Equation (dF/dt)=	Point of Inflection (F^*)	Symmetry
1. Bass (1969)	$(p+qF)(1-F)$	0-0.5	NS
2. Gompertz	$qF \ln(1/F)$	0.37	NS
3. Logistic	$qF(1-F)$	0.5	S

2.4 The Multi-level Substitution Models

Multi-level substitution is a phenomenon in which an initial product may be substituted by a second product while the second one is being replaced by a third one and so on.

Norton and Bass (1987) suggested a model which encompassed and incorporated both diffusion and substitution effects. The original formulation appears conceptually sound and seems to capture the essence of the process. This model, based on the Bass Model (1969), can address the level of sales (absolute sales level) of product generations.

Norton and Bass (1992) stated that the new product in a product family had the regular pattern (i.e., S-curve). They assumed that:

- (1) For a given technology, the advent of a new technological generation eventually drives sales of the earlier generation to approximately zero.
- (2) The process repeats for all succeeding generations.
- (3) The demand for an earlier generation did not peak immediately after introduction of a later generation. Rather, because of the later generation's diffusion process, demand for the earlier generation continued to grow for a brief period before declining.
- (4) The parameters governing the pace of growth and substitution of successive generations of technologies were usually, but not always, constant across generations.

Norton and Bass (1987) gave a model for successive generations of high-innovation products, whereby multiple diffusion curves occur simultaneously. In Section 2.5.1, this

model is discussed.

2.5 Model Selection

The Norton and Bass Model (1987) and Kumar Model (1996) made an assumption that multi-level substitution follows an S-shaped curve. Therefore, these models were selected for this study. The Brockhoff Model (1967) was selected because it denoted a substitution process as the reason for declining sales in the latter stages of the product life cycle. The complementary and substitutive effects between the products under consideration can be reflected. Based on the above-mentioned, these models are discussed in detail in the next Section.

2.5.1 Norton and Bass Model (1987)

Norton and Bass (1987) make the strong assumption that two parameters, p and q , are constant for a series of innovations within the same product class. They stated that, in summary, the model assumed (1) the existence of a series of advancing generations, (2) the substitution of actual and potential sales from earlier generations to later generations, (3) a density function of time to adoption for each generation that applies against a time-varying potential, and (4) constant diffusion parameters across generations of the same product class.

This model deals with four generations of technology simultaneously. It can be

written as follows:

$$\begin{aligned}
 S_1(t) &= F_1(t)m_1[1 - F_2(t - \tau_2)], \\
 S_2(t) &= F_2(t - \tau_2)[m_2 + F_1(t)m_1][1 - F_3(t - \tau_3)], \\
 S_3(t) &= F_3(t - \tau_3)[m_3 + F_2(t - \tau_2)[m_2 + F_1(t)m_1]][1 - F_4(t - \tau_4)], \\
 S_4(t) &= F_4(t - \tau_4)[m_4 + F_3(t - \tau_3)[m_3 + F_2(t - \tau_2)[m_2 + F_1(t)m_1]]],
 \end{aligned} \tag{2.10}$$

where

m_i = the incremental potential served by the i th generation,

$S_i(t)$ = shipments of generation i in time period t .

τ = the time at which the i th generation is introduced, e.g. $F_2(t - \tau_2) = 0$

for $t < \tau_2$,

$$F_i(t) = [1 - \exp(-b_i t)] / [1 + a_i \exp(-b_i t)],$$

$$a_i = q_i / p_i \text{ and } b_i = p_i + q_i$$

where $F_i(t)$ is the fraction of the ultimate potential which has adopted by time t , p is called the coefficient of innovation and q is the coefficient of imitation.

2.5.2 Model Suggested by Kumar (1996)

Kumar (1996) has developed generalized multi-level substitution models. These models, which deal with multilevel substitution for a new product, are based on some single-level substitution models. For instance, one of them, which is called the Kumar Model (1996), is based on the Bass Model. Kumar assumes that each successive generation would

obtain sales by i) external influence, ii) internal influence, and iii) capturing sales that could have otherwise gone to earlier generations.

In the case of three generations, the model can be expressed as

$$\begin{aligned}\frac{df_1}{dt} &= (p_1 - q_1 f_1 - k_1 f_1 f_2 - k_2 f_1 f_3)(1 - f_1) \\ \frac{df_2}{dt} &= (p_2 - q_2 f_2 - k_1 f_1 f_2 - k_2 f_2 f_3)(1 - f_2) \\ \frac{df_3}{dt} &= (p_3 - q_3 f_3 - k_1 f_1 f_3 - k_2 f_2 f_3)(1 - f_3)\end{aligned}\quad (2.11)$$

where p_i and q_i are parameters which are called the coefficients of innovation and imitation.

k_i reflects the influence of sales of product(s) j ($j > i$) on the sales of product i .

$$f_i = N_i(t)/N,$$

N = upper limit on the number of adopters for innovation i ,

N_i = cumulative number of adopters of innovation i at time t .

2.5.3 The Brockhoff Model

The Brockhoff (1967) presented a diffusion model to forecast the sale of different products by the same manufacturer.

The model is expressed by the equation

$$S_t = at^b e^{-ct} + dR_t \quad (2.12)$$

For multi-level substitution, the model is given by the equation

$$S_t = at^b e^{-ct} + dR_t + gR_t^* \quad (2.13)$$

Where $S(t)$ = sales of one generation product in time period t .

a = indicator of general adoption attitude.

b = factor of imitation.

c = factor of substitution.

R_t = sum of sales of related product from the same company.

R_t^* = sum of sales of another product from the same company.

d and g = parameters indicating the complementary of substitutional product.

This model can be a symmetric or nonsymmetric diffusion curve.

Chapter 3

Research Problem and Objectives

3.1 Research Problem

There is an urgent need for solid research on diffusion and substitution models to help better direct R&D efforts, plan material and human resources, as well as assist in developing marketing strategy. In a competitive environment, the rate of adoption of new products speeds up. It is important for the firm to forecast sales of new products, especially that of the product family.

However, so far there is a shortage of research on multi-level substitution models. In the literature review, only four papers (Brockhoff 1967; Norton and Bass 1987; Norton and Bass 1992; Mahajan and Muller 1996) address this topic. The preliminary test results (Appendix B) of the Norton and Bass Model do not fit the data of DRAM well.

For the above-mentioned fact, researchers should develop new multi-level substitution models and analyse the weaknesses of existing multi-level substitution models for forecasting a series of technological substitutions.

In light of the above discussion, this research focused on building new multilevel substitution models and comparing new models with existing ones.

3.2 Research Objectives

The objective of this thesis is to investigate the diffusion and substitution process of high technology products. The study include: (1) testing the existing models employing two data sets, (2) giving a new approach to develop substitution models for forecasting sales of a latest generation product, and (3) comparing the predictive ability of existing models with that of new models.

3.2.1 The New Multilevel Substitution Model

In order to more accurately forecast new product sales, it is necessary to develop a new multilevel substitution model. In this study, an approach to developing a new multilevel substitution model is given. The new model is constructed as follows:

- (1) New models are built on existing models.
- (2) The parameters of the growth rate (e.g. parameters of p_i and q_i in the new model which is based on Bass Model) are not constant in different product generations. The internal and external influence parameters, p_i and q_i change with different product generations.
- (3) Using regression analyses, parameters (p_{i-1} and q_{i-1}) for a new generation product are predicted based on p_i and q_i . In other word, the p_i and q_i are regressed against generation number; then a higher generation number is used to product p_{i-1} and q_{i-1} value associated with that generation number.
- (4) The SSE, MSE, RMSE, R-square, and adjusted R-square are reported for regression

model. The parameters of tested models are estimated, also the standard error and t ratio are presented respectively.

(5) The physical upper limit of sales M_i increases for the new generations of products. M_{i-1} is predicted by regression analysis. The new models are discussed in details in Section 5.4.

Chapter 4

Research Methodology

The methodology of the study can be briefly summarised as follows. Selected models are applied to sales data of a high-tech product family (DRAMs) and tire cord textile in order to empirically test the applicability of describing and predicting. The data was collected from Integrated Circuit Engineering Corporation (ICE), Semiconductor Industry Association (SIA) and Merino (1990). A Nonlinear least squares (NLS) estimation procedure was employed to estimate the models' parameters.

4.1 Semiconductor Industry and DRAM

The reasons for selecting DRAM data as test data set are simple. Firstly, The integrated circuit (IC) industry is big business. The electronics industry is currently at about \$330 billion in sales and the core of the electronics industry is the integrated circuit industry with \$59 billion in world-wide sales. More significantly the automobile and aerospace industries are increasingly end users of integrated circuits.

In the area of improvements in process technology, the shift to computer aided design (CAD), and computer aided manufacturing (CAM) could not take place without the use of integrated circuits in the computers. The current shift to computer integrated manufacturing (CIM) will require even more powerful integrated circuits. Similar trends are

occurring in industries ranging from steel to aerospace and pharmaceutical. Consequently, improvements in those industries are being tied more closely to improvements in the integrated circuit industry.

Secondly, DRAM products are very competitive products. It should be noted that the competition from Japan has occurred primarily in the memory segment of the integrated circuit industry, particularly DRAMs. US firms lost dominance in terms of world market share, in this market segment five years before losing their dominant position in the overall integrated circuit world market. The crossover in the DRAM segment between Japanese and United States firms occurred in 1982 and the slide down in market share for the US has continued through 1989 (Dataquest, 1989). In the semiconductor industry the dynamic of continuous innovation focuses above all on the development and deployment of new technologies. Innovation, however, is not simply a matter of technology development. In addition to new product and process technologies, innovation involves the simultaneous development of new work practices, new markets, and new uses for these technologies. Since the late 1980s, profit margins for DRAMs and other high-volume products have narrowed further with the entry of South Korea as an additional provider.

The widespread diffusion of semiconductor technology has already had a profound affect on many aspects of life. Several authors have suggested that semiconductors provide the foundation for a new techno-economic paradigm that will redefine the path of global economic change and development (Dosi 1982; Freeman 1987; Perez 1985).

Thirdly, DRAMs play an important role in the IC industry. It is considered as one of the key products for developing process technologies, which are used in manufacturing other integrated circuit devices. The products in the integrated circuit industry are broadly classified into two major groups, logic and memory devices (Wilson, Ashton and Egan, 1980). All memory devices, such as DRAMs, store information in the form of bits on the device. All logic devices, such as microprocessors, are associated with the processing of these bits or information; that is, manipulating the bits of information according to some set of instructions to perform some tasks. The memory segment is dominated by the DRAM device.

4.2 Tire Cord Textiles

Tire cord textiles, includes cotton, rayon, nylon, and polyester products were chosen as another data set in the research. Kovac (1969) describes the tire cord market as a mature market where there has been clear cut substitutions of rayon for cotton; nylon for rayon; and polyester starting the substitution cycle for nylon. He also stressed that this transition/replacement of one tire textile for another is influenced by the physical upper limits of the material as well as the cost/performance generated by product/process research. Kovac (1969) estimated that the life cycle of tire cord was about 35 years. A new tire cord fabric is introduced every 10 to 15 years. In comparison with DRAMs, tire cord textiles has a longer life cycle.

4.3 Data Collection

The purpose of this thesis is to empirically test the applicability of multilevel substitution models for describing and predicting the sales of new DRAM products and tire cord textiles. To test these models, DRAM unit sales data was collected from (McClean 1993) and World Semiconductor Trade Statistics (1994). ICE was established in 1964. One of its services is to provide market research such as pricing, technology trends, supplier surveys, product availability and forecasting in the electronic product field. SIA provides information on orders and shipments of world wide semiconductor manufacturers in world market. It contains detailed data for major product families, key product lines, shipments and order data reported by companies worldwide and aggregate data estimated for non-reporting organization, including monthly and yearly summaries.

DRAM devices are high-tech products, which are sold to industrial as well as consumer markets, and they can be used in various applications, such as, computer products, consumer products (VCR, TV), communication equipment, industrial instrument, military devices and so on.

The data employed in this thesis covers six generations of DRAM products from 1975 to 1993. They are 4K bit device (1975 to 1983), 16K bit device (1977 to 1986), 64K bit device (1980 to 1992), 256K bit device (1983 to 1993), 1M bit device (1986 to 1993) and 4M bit device (1989 to 1993). All of them represent annual sales data (see Figure 2-2).

The tire cord textiles shipments data was published in Merino's article (1990). The data set of tire cord textiles includes four generations of products from 1910 to 1979 (see Figure 2-3). The data of cotton tire cord is from 1910 to 1955. The data of rayon tire cord is from 1938 to 1979. The data of nylon tire cord is from 1947 to 1979 and the data of polyester tire cord is from 1962 to 1979.

4.4 Data Analysis Procedure

The models to be tested are the Norton and Bass Model (1987), the model suggested by Kumar (1995), the Brockhoff Model (1967) and the new models developed in this study. The research concentrated on whether these models could be employed to describe and predict the sales of DRAM products and tire cord textiles. Finally, the usefulness of these models was evaluated.

4.4.1 Parameter Estimation

The parameters of each model were estimated using both DRAM data and tire cord textiles data. In general, three estimation procedures can be used: ordinary least squares (OLS), maximum likelihood estimation (MLE) and nonlinear least squares (NLS). Schmittlein and Mahajan (1982) stated that the OLS procedure have a time-interval bias because discrete time-series data is used for estimating a continuous model. Srinivasan and Mason (1986) pointed out that because the MLE procedure considered only sampling errors

and ignored all other errors (i.e., the effects of excluded marketing variables that influence the diffusion process), it underestimated the standard errors of the estimated parameters. This resulted in possible wrong inferences about the statistical significance of the parameters. Berkson (1955) showed that in many situations commonly encountered in statistical practice in estimating logistic functions, the minimum χ^2 and MLE were identical. Srinivasan and Mason (1986) suggested employing the NLS estimation procedures to estimate the parameters of diffusion and substitution models. Mahajan, Mason, and Srinivasan (1986, p.213) concluded that the non-linear least squares estimation procedure gives the best results among the three methods.

The nonlinear three-stage least squares (3SLS) procedure in SYSNLIN from the Statistical Analysis System (SAS) software package was utilized to simultaneously estimate all parameters in the models considered. The SYSNLIN procedure combines iterative minimization methods for nonlinear regression with specialized estimation techniques for simultaneous equation systems to estimate parameters in a simultaneous system of nonlinear equations (SAS 1984, pp. 506).

Various statistical measures were applied in order to evaluate the models. No matter what method is used to generate a projection, the major barometer of success in forecasting is accuracy. The Null hypothesis is that coefficients of the parameters (i.e., p and q) are equal to zero.

The Mean Squared Error (MSE), Root mean Squared Error (RMSE), Sum of Squared Error (SSE), Coefficient of Determination (R^2) and adjusted R^2 were calculated. The Standard Error of the regression point production was reported and 95% confidence interval was used for prediction as well. Model fit was reported by MSE. In this way the MSE of the different model could be compared on an equivalent unit basis.

Chapter 5

Results of the Study

In this section, testing results of selected models and new models are given. Section one reports testing results of the Norton and Bass Model (1987). Section two provides the testing results of the Kumar Model (1996). Section three presents testing results of the Brockhoff Model (1967). Section four introduces a new approach of modelling and shows the testing results of new models based on the Bass Model (1969), the Gompertz and the Logistic Model respectively.

It is necessary to highlight the data characteristics before reporting the results of testing. The Tire Cord data set includes four generations of products. The observations of cotton (hereafter T1), rayon (T2), nylon (T3), and polyester (T4) have 46, 39, 30 and 15 data points respectively. In contrast with Tire Cord data set, the DRAM data set has only 9, 10, 13, 10, 7 and 5 data points for generation 4K (hereafter D1), 16K (D2), 64K (D3), 256K (D4), 1M(D5) and 4M(D6) products respectively. Model fit is reported by SSE, MSE and R^2 in terms of the cumulative sales data except for the Brockhoff Model, which deals with non-cumulative sales data. Once parameters are estimated, forecasting can be done by letting $t = n+1, n+2, \dots$, where t is the time parameter ($t = 1, 2, 3, \dots, n$) and n is the number of observations used to estimate the parameters of the tested models. In this thesis, two measures of forecast accuracy were employed:

(1) The $t-1$ observations were used one step ahead to forecast the ' t ' th data point for DRAM

1M and 4M products. In other words, a hold out sample of the last one data point was set aside for a forecast comparison.

(2) The $t-3$ observations were used three steps ahead to forecast $t-2$, $t-1$, and t data points for the Tire Cord data set.

The forecasting results are reported by terms of error and percentage error. It should be noted that the data for DRAMs is in millions of units and that of Tire Cord in millions of pounds. The numbers describing and predicting results of tested models are provided in Tables 5-1 to 5-50. From these results, we can find out how the selected and new models fit onto the DRAM and Tire Cord data sets.

5.1 Testing Results of Norton and Bass Model (NBM)

The Norton and Bass Model (1987) (NBM) presented in Section 2.5 can handle four product generations simultaneously. Four regressions were tested in this section. The first test is performed on the NBM for D1 to D4, and the results are given in Table 5-1 and 5-2. The second test has been done on D2 to D5. Test results are given in Tables 5-3 and 5-4. Similarly, the third test was run on D3 to D6. Test results are presented in Tables 5-5 and 5-6. The last test dealt with Tire Cord sales data. The test results are given in Tables 5-9 and 5-10. From these results, we can see that NBM fits the data well. In tests 1, 2, and 3, the R^2 varies between 0.8524 and 0.9945. All t ratios are greater than 4.17 indicating the models' significance.

Tables 5-7 and 5-8 show the forecasting results of DRAM 1M and 4M products in 1993. Tables 5-11 and 5-12 provide the forecasting results of nylon(T3) and polyester (T4) products from 1977 to 1979. Each test estimated 6 parameters.

Table 5-1: Nonlinear 3SLS Summary of Residual Errors for DRAM (D1- D4)
using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D1	21482	1245.3	35.28920	0.8524	0.8545
D2	180161	10649.9	103.19854	0.9572	0.9569
D3	959861	58468.7	241.80306	0.9595	0.9581
D4	1469056	95290.1	308.69094	0.9666	0.9631

Table 5-2: Nonlinear 3SLS Parameter Estimates for DRAM (D1- D4)
using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p	0.025894	0.0023548	11.00	0.0001
q	0.180515	0.02058	8.77	0.0001
m ₁	1011.63	43.51637	23.25	0.0001
m ₂	2826.52	115.76634	24.42	0.0001
m ₃	5515.26	340.87384	16.18	0.0001
m ₄	5294.57	553.28892	9.57	0.0001

Table 5-3: Nonlinear 3SLS Summary of Residual Errors for DRAM (D2- D5)

using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D2	546996	31709.9	178.07274	0.8699	0.8718
D3	680546	40229.3	200.57251	0.9713	0.9712
D4	585079	35639.3	188.78381	0.9867	0.9862
D5	112559	7301.1	85.44645	0.9915	0.9906

Table 5-4: Nonlinear 3SLS Parameter Estimates for DRAM (D2- D5)

using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p	0.017972	0.0011923	15.07	0.0001
q	0.306797	0.01592	19.27	0.0001
m ₂	3337.66	148.96263	22.41	0.0001
m ₃	4390.91	243.32105	18.05	0.0001
m ₄	5893.33	435.80478	13.52	0.0001
m ₅	2446.44	380.87708	6.42	0.0001

Table 5-5: Nonlinear 3SLS Summary of Residual Errors for DRAM (D3- D6)

using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D3	1008864	58484.9	241.83649	0.9575	0.9581
D4	475730	28122.0	167.69601	0.9892	0.9891
D5	72299	4404.0	66.36270	0.9945	0.9943
D6	20888	1354.9	36.80896	0.9524	0.9475

Table 5-6: Nonlinear 3SLS Parameter Estimates for DRAM (D3- D6)

using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p	0.013399	0.0008279	16.19	0.0001
q	0.388946	0.01588	24.49	0.0001
m ₃	6705.05	211.44437	31.71	0.0001
m ₄	4975.72	353.21008	14.09	0.0001
m ₅	3112.43	411.63352	7.56	0.0001
m ₆	1273.95	305.65259	4.17	0.0008

Based on test 3, the results of forecasting (DRAM 1M and 4M in 1993) are given in Tables 5-7 and 5-8.

Table 5-7: Forecasting of D5 (1993) with 95% confidence interval using the NBM

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	3609	3694.14	3625.60	3762.67	-85.14	-2.36

Table 5-8: Forecasting of D6 (1993) with 95% confidence interval using the NBM

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	1466	1674.99	1674.99	1674.99	-208.99	-14.26

Table 5-9: Nonlinear 3SLS Summary of Residual Errors for Tire Cord (T1-T4)
using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
T1	5630327	84986.1	291.52371	0.9862	0.9862
T2	9965202	151178.8	388.81717	0.9796	0.9796
T3	1271849	19442.3	139.43555	0.9885	0.9884
T4	584920	9080.3	95.29039	0.9429	0.9415

Table 5-10: Nonlinear 3SLS Parameter Estimates for Tire Cord (T1-T4)

using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p	0.00470926	0.0001136	41.46	0.0001
q	0.066305	0.0014810	44.77	0.0001
m ₁	12589.55	129.64455	97.11	0.0001
m ₂	12649.90	305.15885	41.45	0.0001
m ₃	4300.08	359.85537	11.95	0.0001
m ₄	8670.06	455.69850	19.03	0.0001

Table 5-11: Forecasting of T3 (1977-1979) with 95% confidence interval

using the NBM

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	4947	4892.76	4864.09	4921.43	54.24	1.10
1978	5210	5061.89	5024.06	5099.72	148.11	2.84
1979	5490	5199.82	5149.49	5250.15	290.18	5.29

Table 5-12: Forecasting of T4 (1977-1979) with 95% confidence interval

using the NBM

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	2155	1777.57	1080.05	2475.10	377.43	17.51
1978	2408	2009.41	191.81	3827.00	398.59	16.55
1979	2635	2263.47	-1702.38	6229.31	371.53	14.10

5.2 Testing Results of The Model Suggested by Kumar (1996)

The "Kumar Model", which deals with three generations of products simultaneously, was presented in Equation 2.11. In this model 9 parameters need to be estimated but the DRAM sales database does not provide a sufficient number of observations. So, the tests of DRAM products does not converge.

When we tested the Tire Cord database, the situation improved. One of the two tests was convergent. In test 1, we loaded T1 (46 observations), T2 (35 observations), and T3 (26 observations). The results of test (T1, T2 and T3) are shown in the Tables 5-13 and 5-14. Unfortunately, in another test, if we loaded data T2 (35 observations), T3 (26 observations) and T4(11 observations), the test did not converge (i.e., the test does not meet the predetermined criteria found in SAS).

Table 5-13: Nonlinear 3SLS Summary of Residual Errors for Tire Cord (T1-T3)
using the Model suggested by Kumar

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
T1	151235	2400.5	48.99539	0.7315	0.7188
T2	315473	5007.5	70.76372	0.7209	0.7077
T3	26389	418.88	20.46653	0.9682	0.9667

Table 5-14: Nonlinear 3SLS Parameter Estimates for Tire Cord (T1-T3)

using the Model suggested by Kumar

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p_1	0.014557	0.0019487	7.47	0.0001
p_2	0.00265522	0.0014079	1.89	0.0639
p_3	0.00577939	0.0027617	2.09	0.0404
q_1	0.024571	0.0042574	5.77	0.0001
q_2	0.064847	0.01116	5.81	0.0001
q_3	0.174824	0.0070735	24.72	0.0001
m_1	6492.36	1.00993	6428.54	0.0001
m_2	7758.48	68.29640	113.60	0.0001
m_3	1105.57	137.49083	8.04	0.0001
k_1	0.068711	0.0071008	9.68	0.0001
k_2	0.000043264	2.06963E-6	20.90	0.0001
k_3	0.00402659	0.0022818	1.76	0.0825

As shown in Tables 5-15 and 5-16, R^2 is between 0.7209 and 0.9682, also the 't' ratio of k_3 and p_2 is less than 2. Since the test 2 (T2, T3 and T4) does not converge, no forecasting is provided.

5.3 Testing Results of the Brockhoff Model (1967)

The Brockhoff Model (1967) is given by equation (2.13). It did converge when we employed DRAMs (64K, 256K, 1M and 4M) non-cumulative sales data (DS3, DS4, DS5 and

DS6) for testing respectively. Table 5-15 to 5-20 show the testing results of DS3, DS4 and DS5. The values of R^2 are fall into range 0.9622 to 0.9985. However, the 't' ratio varies from -0.02 to 4.82. When we tested DS6, only 4 observations were available, parameter estimation was abandoned by the SAS. The possible reason is that too many parameters had to be estimated and few data points were provided. The prediction result of DS5 is shown in the Table 5-21 based on estimated parameters.

For the Tire Cord product family, the Tire Cord non-cumulative sales data (TS2, TS3 and TS4) was used to test this model. The regression results of TS2 are shown in Tables 5-22 to 5-27.

Table 5-15: Nonlinear OLS Summary of Residual Errors for DRAM(D3)
using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
DS3	25178	4196.4	64.77931	0.9622	0.9307

Table 5-16: Nonlinear OLS Parameter Estimates for DRAM(D3)

using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	0.000057252	0.0001929	0.30	0.7766
b	26.104109	5.41963	4.82	0.0029
c	5.123199	1.07500	4.77	0.0031
g ₄	0.219756	0.08219	2.67	0.0368
g ₅	-0.141199	0.16361	-0.86	0.4213
g ₆	0.514558	0.88378	0.58	0.5816

Table 5-17: Nonlinear OLS Summary of Residual Errors for DRAM(D4)

using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
DS4	9868	2467.0	49.66912	0.9885	0.9741

Table 5-18: Nonlinear OLS Parameter Estimates for DRAM(D4)

using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	4.409949	6.48050	0.68	0.5335
b	5.708566	3.13563	1.82	0.1428
c	0.804539	0.74957	1.07	0.3436
g ₃	0.017373	0.07501	0.23	0.8282
g ₅	-0.649312	1.28083	-0.51	0.6389

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
g_6	-0.00846062	0.43280	-0.02	0.9853

Table 5-19: Nonlinear OLS Summary of Residual Errors for DRAM(D5)

using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
DS5	1161	580.63141	24.09629	0.9985	0.9954

Table 5-20: Nonlinear OLS Parameter Estimates for DRAM(D5)

using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	3.984578	4.69546	0.85	0.4855
b	6.114866	2.07240	2.95	0.0982
c	0.937244	0.44921	2.09	0.1722
g_4	-0.00307307	0.04435	-0.07	0.9511
g_6	-0.015437	0.44689	-0.03	0.9756

Table 5-21: Forecasting of D5 (1993) using the Brockhoff Model

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	590	723.1	624.23	821.98	-133.1	-22.56

Table 5-22: Nonlinear OLS Summary of Residual Errors for Tire Cord (TS2)
using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
TS2	24036	728.35766	26.98810	0.9600	0.9539

Table 5-23: Nonlinear OLS Parameter Estimates for Tire Cord (TS2)
using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	0.00298885	0.0041466	0.72	0.4761
b	6.742825	0.81036	8.32	0.0001
c	0.435970	0.05452	8.00	0.0001
g ₁	0.025377	0.05665	0.45	0.6571
g ₃	0.405706	0.09934	4.08	0.0003
g ₄	-0.244063	0.11080	-2.20	0.0347

The testing results of TS3 are shown in Tables 5-19 and 5-20.

Table 5-24: Nonlinear OLS Summary of Residual Errors for Tire Cord (TS3)
using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
TS3	3560	148.32428	12.17885	0.9911	0.9892

Table 5-25: Nonlinear OLS Parameter Estimates for Tire Cord (TS3)
using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	0.000060384	0.00008273	0.73	0.4725
b	7.136244	0.70528	10.12	0.0001
c	0.305697	0.04013	7.62	0.0001
g ₁	-0.067198	0.04661	-1.44	0.1623
g ₂	0.047634	0.02003	2.38	0.0257
g ₄	0.082995	0.13696	0.61	0.5502

Tables 5-26 and 5-27 report the testing results of regression of TS4.

Table 5-26: Nonlinear OLS Summary of Residual Errors for Tire Cord (TS4)
using the Brockhoff Model

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
TS4	4671	467.09364	21.61235	0.9685	0.9559

Table 5-27: Nonlinear OLS Parameter Estimates for Tire Cord (TS4)

using the Brockhoff Model

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
a	0.051656	0.23651	0.22	0.8315
b	5.258264	2.89161	1.82	0.0990
c	0.388038	0.24009	1.62	0.1371
g_2	-0.042957	0.32660	-0.13	0.8980
g_3	0.029908	0.34642	0.09	0.9329

Above, the Brockhoff Model describes the Tire Cord data well . The $R^2 = 0.9600$, 0.9911, and 0.9685 when regression analysis is conducted on rayon (TS2), nylon (TS3) and polyester (TS4) products respectively.

The results of forecasting are also given according to the above parameters as shown in Tables 5-28 and 5-29.

Table 5-28: Forecasting of TS3 (1977-1979) with 95% confidence interval

using the Brockhoff Model

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	240	234.07	203.31	264.83	5.93	2.47
1978	263	220.21	188.52	251.91	42.79	16.27
1979	280	205.97	173.37	238.57	74.03	26.44

Table 5-29: Forecasting of TS4 (1977-1979) with 95% confidence interval
using the Brockhoff Model

Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	258	229.04	166.66	291.41	28.96	11.22
1978	253	214.01	142.07	285.96	38.99	15.41
1979	227	196.39	115.09	277.70	30.61	13.48

5.4 Testing Results of the New Multilevel Substitution Model

In this study, a new multilevel substitution model is constructed from each of the Bass, Gompertz, and Logistic Models. We assume that the parameters of the growth rate (e.g., parameters of p_i and q_i in Bass Model) are not constant in different product generations. The internal and external influence parameters, p_i and q_i change with different product generations. Based on the values of p_i , q_i , and M_i parameters, p_{i-1} , q_{i-1} and M_{i-1} for a new generation could be predicted. The p_i , q_i and M_i are regressed against the generation number; then a higher generation number is used as a start point to predict p_{i-1} , q_{i-1} and M_{i-1} values associated with that generation number. Those p_{i-1} and q_{i-1} values are adjusted by running a simulation program which minimizes SSE between actual and forecasting sales. Additionally, the prediction of each model with 95% confidence interval is also provided. It should be noted that those prediction are calculated based on NLS procedure. The SSE, MSE, RMSE, Coefficient of Determination (R^2) and adjusted R^2 of the regression analysis are reported.

5.4.1 Estimate Physical Upper Limit M

The physical upper limit of sales M_i must be less than M_{i-1} (see Figures 2-4 and 2-5). From DRAM sales data, DRAM 4K (M_1) = 275, 16K (M_2) = 1129, and 64K (M_3) = 2645 millions unit respectively. $M_4 = 4450$ is estimated from the sales pattern of previous product generations. In other word, we assume the increase rate of M_i is constant. Here, regression analysis (Using Tablecurve 3.1* software) is performed by the following equation,

$$M = a + \left(\frac{1}{2}\right)b\left(1 + \operatorname{erf}\left(\frac{t-c}{\sqrt{2}d}\right)\right) \quad (5.1)$$

$a = -144.74299$, $b = 7164.5459$, $c = 3.43369668$, and $d = 1.5554242$.

From the Tablecurve software, the Equation (5.1) fits the M_1 to M_4 with $R^2 = 1$.

Employing equation (5.1), $M_5 = 5892$ and $M_6 = 6664$ are predicted when we let $t = 5$ and 6 (see Figure 5-1).

Since only two history data points (M_1 and M_2) can be used to estimate M_3 . The following formula is used to calculate M_3 . This formula assumes that the increase rate of M_i is constant.

$$M_3 = \left(\frac{M_2 - M_1}{M_1} + 1\right) M_2$$

When we let $M_1 = 6494$, $M_2 = 7175$, we find $M_3 = 7926$. Similarly, we obtain $M_4 = 8758$.

* Tablecurve 3.1 software can be used to search regression equations which fit the employed data set.

Figure 5-1

5.4.2 The New Model Based on the Bass Model (NMB)

5.4.2.1 Estimation of parameters p_5 and q_5

To obtain p_1 to p_4 and q_1 to q_4 , four parameter fitting regressions are performed. All R^2 s are greater than 0.99. The 't' ratio of p_1 to p_4 and q_1 to q_4 is greater than 2.62. The results from Tables 5-30 to Table 5-32 showed that D1 to D4 fitted the Bass Model very well. The data has been normalized (as shown in Appendix C) for calculation of F. Here F represents proportion of potential adopters who have adopted an innovation up until time t and the value of F lies between 0 and 1.

Table 5-30: Summary of Residual Errors for DRAM (D1, D2, D3 and D4)
using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D1	0.00126	0.0001796	0.01340	0.9990	0.9988
D2	0.00210	0.0002625	0.01620	0.9987	0.9985
D3	0.01611	0.0016112	0.04014	0.9915	0.9906
D4	0.00178	0.0001980	0.01407	0.9989	0.9987

The values of p_1 to p_4 and q_1 to q_4 are shown in Tables 5-31 and 2-32. Two trends are evident. The value of q increases, while that of p decreases (see Figures 5-2 and 5-3).

5.4.2.2 Regression Analysis of p Values

Figure 5-2

Figure 5-3

When p_1 to p_4 are applied to regression analysis (Using Tablecurve 3.1 software), the following equation is obtained.

$$\ln p = a + b \ln t + c / t^2 \quad (5.2)$$

Where $a = -6.77836103$, $b = 1.24011862$, and $c = 2.727306483$.

$R^2 = 0.9999$. When $t = 5$, $p_5 = 0.0093406928$.

Table 5-31: Nonlinear OLS Parameter Estimates for DRAM (p_1 , p_2 , p_3 and p_4)
using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p_1	0.017404	0.0020055	8.68	0.0001
p_2	0.00531683	0.0008719	6.10	0.0003
p_3	0.00601785	0.0022984	2.62	0.0257
p_4	0.00753122	0.0008657	8.70	0.0001

5.4.2.3 Regression Analysis of q Values

Equation (5.3) was found using the Tablecurve 3.1 program when q_1 to q_4 were used.

$$\ln q = a + b \exp t + c \ln (t/t^2) \quad (5.3)$$

Where $a = 0.05321981$, $b = -0.0053079$, and $c = -0.10831697$.

The equation fits the data well. $R^2 = 0.9999$. F value = 161279.43155.

When $t = 5$, $q_5 = 0.4764399$.

Table 5-32: Nonlinear OLS Parameter Estimates for DRAM (q_1 , q_2 , q_3 and q_4)
using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
q_1	1.039615	0.03759	27.65	0.0001
q_2	0.995185	0.03785	26.29	0.0001
q_3	0.935937	0.08660	10.81	0.0001
q_4	0.781925	0.02413	32.40	0.0001

5.4.2.4 Application of Forecasting for 1993 DRAM sales data

The forecasting results of NBM with 95% confidence interval for DRAM 1M (D5) is presented in Table 5-33.

Table 5-33: Forecasting of D5 (1993) with 95% confidence interval using the NBM

Bass Model $F = (1 - (\text{EXP}(-(p + q) * t))) / (1 + (q/p) * (\text{EXP}(-(p + q) * t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	3609	4053.97	3643.05	4464.88	-444.97	-12.33

Using the same method, The sales of 4M DRAM product were predicted. The results are given in Table 5-34.

Table 5-34: Forecasting of D6 (1993) with 95% confidence interval using the NBM

Bass Model $F = (1 - (\text{EXP}(-(p + q) \cdot t))) / (1 + (q/p) \cdot (\text{EXP}(-(p + q) \cdot t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	1466	1975.37	1544.5	2406.24	-509.37	-34.75

Tables 5-35 and 5-36 give the results of regression analysis on Tire Cord products. All R^2 values are remarkably high, the lowest one exceeding 0.9945, and 't' ratio values are greater than 12.61. The Forecasting results are shown in Tables 5-37 and 5-38.

Table 5-35: Summary of Residual Errors for Tire Cord (T1 and T2) using the NBM

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
T1	0.03064	0.0006963	0.02639	0.9945	0.9944
T2	0.02006	0.0005014	0.02239	0.9966	0.9965

Table 5-36: Nonlinear OLS Parameter Estimates for Tire Cord (p_1 , p_2 , q_1 and q_2)

using the NBM

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
p_1	0.00402372	0.0003190	12.61	0.0001
p_2	0.00478846	0.0003736	12.82	0.0001
q_1	0.141401	0.0042134	33.56	0.0001
q_2	0.191517	0.0053333	35.91	0.0001

Table 5-37: Forecasting of T3 (1977-1979) with 95% confidence interval

using the NBM

Bass Model $F = (1 - (\text{EXP}(-(p + q) * t))) / (1 + (q/p) * (\text{EXP}(-(p + q) * t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	4947	5256.26	5076.25	5436.27	-309.26	-6.25
1978	5210	5549.63	5368.01	5731.25	-339.63	-6.52
1979	5490	5823.46	5640.92	6006	-333.46	-6.07

Table 5-38: Forecasting of T4 (1977-1979) with 95% confidence interval

using the NBM

Bass Model $F = (1 - (\text{EXP}(-(p + q) * t))) / (1 + (q/p) * (\text{EXP}(-(p + q) * t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	2155	2423.62	2307.66	2539.58	-268.62	-12.47
1978	2408	2885.17	2742.8	3027.55	-477.17	-19.82
1979	2635	3385.62	3211.48	3559.76	-750.62	-28.49

5.4.3 The New Model Based on Gompertz Model (NMG)

The Gompertz Model is found in equation 2.5 described earlier.

The solution $F = \text{Exp}(-(\text{Exp}(-(c + q * t))))$

Where c is constant. As Tables 5-39 show, R^2 values are greater than 0.9950. Four tests were

run in order to develop Table 5-40. The q_i and c_i are the results from TEST_i.

Table 5-39: Summary of Residual Errors for DRAM (D1, D2, D3 and D4)
using the NMG

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D1	0.00276	0.0003937	0.01984	0.9978	0.9975
D2	0.00780	0.0009752	0.03123	0.9950	0.9944
D3	0.00406	0.0004057	0.02014	0.9978	0.9976
D4	0.00248	0.0002751	0.01659	0.9984	0.9982

Table 5-40: Nonlinear OLS Parameter Estimates for DRAM (q_1 , q_2 , q_3 , q_4 , c_1 , c_2 , c_3 , and c_4) using the NMG

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
q_1	0.757324	0.03265	23.20	0.0001
q_2	0.705056	0.04636	15.21	0.0001
q_3	0.671925	0.02767	24.29	0.0001
q_4	0.556956	0.01747	31.89	0.0001
c_1	-2.500411	0.12432	-20.11	0.0001
c_2	-3.224087	0.23558	-13.69	0.0001
c_3	-3.159102	0.14502	-21.78	0.0001
c_4	-2.830811	0.10019	-28.25	0.0001

The parameter q is coefficient of imitation. The absolute 't' ratio values greater than 13.69.

The prediction of DRAM sales of 1M and 4 M is given in Table 5-41 and 5-42.

Table 5-41: Forecasting of D5 (1993) with 95% confidence interval using the NMG

Gompertz Model $F = \text{Exp}(-(\text{Exp}(-(c+q*t))))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	3609	3749.36	3712.64	3786.08	-140.36	-3.89

Table 5-42: Forecasting of D6 (1993) 95% confidence interval using the NMG

Gompertz Model $F = \text{Exp}(-(\text{Exp}(-(c+q*t))))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	1466	1471.96	1405.27	1538.65	-5.96	-0.41

The Forecasting results of Tire Cord (T3 and T4) is shown in Table 5-43 and 5-44.

Table 5-43: Forecasting of T3 (1977-1979) with 95% confidence interval
using the NMG

Gompertz Model $F = \text{Exp}(-(\text{Exp}(-(c+q*t))))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	4947	4960.6	4925.76	4995.43	-13.6	-0.27
1978	5210	5188.04	5153.02	5223.06	21.96	0.42
1979	5490	5402.7	5367.55	5437.85	87.3	1.59

Table 5-44: Forecasting of T4 (1977-1979) with 95% confidence interval

using the NMG

Gompertz Model $F = \text{Exp}(-(\text{Exp}(-(c+q*t))))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	2155	2296.64	2151.94	2441.33	-141.64	-6.57
1978	2408	2635.45	2474.75	2796.16	-227.45	-9.45
1979	2635	2981.77	2803.39	3160.16	-346.77	-13.16

5.4.4 The New Model Based on Logistic Model (NML)

The Logistic Model is given in Equation 2.3 and the solution $F = 1/(1 + \text{EXP}(-(c+q*t)))$.

Two parameters need to be estimated in each regression analysis. As shown in Tables 5-45 and 5-46, all R^2 's are greater than 0.9909. 't' ratios are greater than 11.38 or less than -11.12.

Table 5-45: Summary of Residual Errors for DRAM (D1, D2, D3 and D4)

using the NML

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
D1	0.00201	0.0002874	0.01695	0.9984	0.9982
D2	0.00234	0.0002924	0.01710	0.9985	0.9983
D3	0.01712	0.0017121	0.04138	0.9909	0.9900
D4	0.00266	0.0002960	0.01720	0.9983	0.9981

Four tests were run in order to develop Table 5-46.

Table 5-46: Nonlinear OLS Parameter Estimates for DRAM (q_1 , q_2 , q_3 , q_4 , c_1 , c_2 , c_3 and c_4) using the NML

Parameter	Estimate	Approx . Std Err	't' Ratio	Approx. Prob> t
q_1	1.096465	0.04243	25.84	0.0001
q_2	1.013324	0.03772	26.86	0.0001
q_3	0.964353	0.08471	11.38	0.0001
q_4	0.809532	0.02722	29.74	0.0001
c_1	-4.291708	0.17188	-24.97	0.0001
c_2	-5.315743	0.20234	-26.27	0.0001
c_3	-5.184567	0.46628	-11.12	0.0001
c_4	-4.789871	0.16549	-28.94	0.0001

The predictive results of D5 and D6 could be found in Tables 5-47 and 5-48. In addition, the forecasting results of T3 and T4 are presented in Table 5-59 and 5-62.

Table 5-47: Forecasting of D5 (1993) with 95% confidence interval

using the NML

Logistic Model $F = 1/(1 + \text{EXP}(-(c+q*t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	3609	4110.33	3632.64	4588.03	-501.33	-13.89

Table 5-48: Forecasting of D6 (1993) with 95% confidence interval using the NML

Logistic Model $F = 1/(1 + \text{EXP}(-(c+q*t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1993	1466	2006.2	1511.71	2500.7	-540.2	-36.85

Table 5-49: Forecasting of T3 (1977-1979) with 95% confidence interval
using the NML

Logistic Model $F = 1/(1 + \text{EXP}(-(c+q*t)))$						
Year	Actual	Forecasting	L 95% cl	U 95% cl	Error	Error %
1977	4947	5318.13	4980.39	5655.88	-371.13	-7.50
1978	5210	5619.7	5279.91	5959.49	-409.7	-7.86
1979	5490	5899.68	5559.11	6240.25	-409.68	-7.46

Table 5-50: Forecasting of T4 (1977-1979) with 95% confidence interval

using the NML

Logistic Model $F = 1/(1 + \text{EXP}(-(c+q*t)))$						
Year	Actual	Forecasting	L 95% ci	U 95% ci	Error	Error %
1977	2155	2497.84	2162.77	2832.92	-342.84	-15.91
1978	2408	3008.91	2602.97	3414.85	-600.91	-24.95
1979	2635	3564.99	3076.16	4053.83	-929.99	-35.29

Chapter 6

Discussion

In Chapter 5, we reported the testing results of the selected and new models. The detailed discussion of the testing results are given in this chapter. An outline of this chapter is as follows. Section 1 describes the tested models and evaluated the models empirically by demonstrating the parameter trends which reflects the growth rate of innovation diffusion. In Section 2, we focused on comparing the predicted results of the tested models and selecting the better forecasting models. The conclusion is presented in the last section.

In this study, we estimated selected models and evaluated three new model forms using the NLS procedure for two data sets. The testing results reveal that the new model based on the Gompertz model has better predictive ability on the DRAM product families. The key factor to establishing a new approach is to use the knowledge of previous generation product sales. This involves determining patterns in the historical record and then projecting the patterns into the future.

The visual examination of the cumulative sales curve (see Figures 2-4 and 2-5) for DRAM's and Tire Cord fabrics, shows that the cumulative sales data indeed has an S-shaped curve. This confirmation determines that the research should employ S-shaped curve models such as the Bass Model. To estimate the parameters of the models tested for each data set, a nonlinear least squared method analogous to that proposed by Srinivasan and Mason

(1986) for the Bass model, is employed. The theoretical cumulative sales curve is differentiated to give the estimated sales for each period, with the parameters selected to minimize the sum of squared error.

6.1 Description of Selected Models

In Chapter 5, we tested the Norton and Bass Model (1987), the Kumar Model (1996), the Brockhoff Model (1967) and the new models based on the Bass, Gompertz, Logistic Models respectively. These models focus on the development of an S-shaped curve and serve to depict and predict sales of innovations.

The Norton and Bass Model (NBM) deals with multiple generations of a product. Their approach considers displacement of preceding generations by a new generation of the product. As shown in Tables 5-1, 5-3 and 5-5, the NBM fits the DRAM data well. The minimum $R^2 = 0.8524$. In addition, the minimum 't' ratio = 4.17 (m_6).

It should be noted that the parameters, p and q , are not constant (see Tables 5-2, 5-4, and 5-6) in three different tests. The values of m_2 , m_3 , and m_4 have been changing in three tests as well. However, Norton and Bass (1987) stated that the very strong assumption that p and q were constant across equations should be easily falsifiable on the basis of model fit. If the p_i and q_i are really different for different i , it should be difficult to obtain reasonable fits to the empirical data and reasonable forecasts using the simpler model. The tests on T1-

T4 (see Table 5-9) also show $R^2 > 0.94$ and that all 't' ratios of the estimated parameters exceed 11.95.

The Kumar Model (1996) has similar theoretical considerations to the Norton and Bass Model, in which each successive generation obtains sales not only by external and internal influences but also by capturing sales that could have otherwise gone to earlier generations. Tables 5-13 indicates that $R^2 > 0.72$ on test of Tire Cord products (T1-T3). When we tested DRAM products and Tire Cord (T2-T4), the model did not converge.

The Brockhoff Model did not converge on DRAM product (DS6). Table 5-15 to 5-20 show tested results on DS3, DS4 and DS5. The R^2 is higher than 0.96. When we applied it to test Tire Cord non-cumulative sales data (TS2, TS3 and TS4), it fitted the data set well. R^2 was between 0.96 and 0.9911.

When DRAM data sets were applied to test selected models, they did not converge in some parameter estimation procedure for the Brockhoff and Kumar Models, but these two models did converge on Tire Cord data set. Obviously, the Tire Cord data set had more observations for each product generation than that of DRAM data set. The reason for non-convergence for these two models might be that too many parameters needed to be estimated with too few observations available, or, it might be the SAS/NLS algorithm has problems that alternative algorithm might not have.

Table 5-30 shows that the model based on the Bass Model (NMB) that fits the DRAM data set well. R^2 exceeds 0.9915 and 't' ratio of estimated parameters was greater than 2.62 (see Tables 5-31 and 5-32). NMG fits the DRAM(D1, D2, D3, and D4) very well. R^2 is between 0.995 and 0.9984 (see Table 5-39). The 't' ratio of q_i and c_i ($i=1$ to 4) exceeds 15.21 or less than -13.69 (see Table 5-40). Table 5-45 shows that the NML also has a higher R^2 value, when applied to DRAM (D1, D2, D3 and D4). The 't' ratio of q_i and c_i either exceeds 11.38 or is less than -11.12.

In some diffusion models, the upper limit of sales needs to be estimated. This affects the validity of the tested model. Fortunately, when we estimated m_5 and m_6 of DRAM, 4 previous sets of sales data were available. We used nonlinear regression analysis to estimate the upper limit of sales. The assumption was that the potential adopting population was not constant.

From a statistical point view, the new models fits the data of DRAM and Tire Cord products better than other tested models given that R^2 approaches 1. Observing Tables 5-31 and 5-32, the growth trend of a parameter's value is clear, q values decreases while p values increase over product generations. Tables 5-40 and 5-46 show that q in the NMG and the NML, coefficient of imitation, also declined. The implications of these results are that the growth of p values is mainly driven by external influences, such as advertising and promotion. Decrease in q values are affected by internal influence (i.e. word of mouth). This finding provides the foundation for developing a new model. Furthermore, It could be used

as the base of strategic formulation for firms.

6.2 Prediction of Selected Models

In this section, we discuss the predictive results of the tested models. For comparison purposes, Tables 6-1 to 6-4 are created. All forecasting results are from Chapter 5. In this thesis, one step and three steps ahead forecasting techniques were applied to DRAM (D5 and D6) and Tire Cord (T3 and T4) respectively. The fitted tested model (parameters have been estimated) is used as an input function for the forecasting model, and a better model provides most accuracy. It should be noted that when a model predicts the latest sales volume (i.e. DRAM 1M, 1993), the actual data is kept apart and the data up to then (1975-92) used as the basis for forecasting 1993. The better models are those that provided forecasts for 1993 which are closer to the actual sales volumes. This is the main reason for comparing the models in this way. In general, the test is independent in the sense that the data being forecast are not used in establishing the forecasting model.

Table 6-1: Comparison of Prediction Results (DRAM 1M Cumulative Sales in 1993)

Model	Actual	Forecasting	Absolute error	Rank
NBM	3609	3694.14	85.14	*
NMB	3609	4053.97	444.97	***
NMG	3609	3749.36	140.36	**
NML	3609	4110.33	501.33	****

Table 6-2: Comparison of Prediction Results (DRAM 4M Cumulative Sales in 1993)

Model	Actual	Forecasting	Absolute error	Rank
NBM	1466	1674.99	208.99	**
NMB	1466	1975.37	509.37	***
NMG	1466	1471.96	5.96	*
NML	1466	2006.2	540.2	****

Table 6-3: Comparison of Prediction Results (Tire Cord T3 Cumulative Sales in 1977-1979)

Year	Actual	NBM	NMB	NMG	NML
1977	4947	4892.76 (54.24) **	5256.26 (309.26) ***	4960.6 (13.6) *	5318.13 (371.13) ****
1978	5210	5061.89 (148.11) **	5549.63 (339.63) ***	5188.04 (21.96) *	5619.7 (409.7) ****
1979	5490	5199.82 (290.18) **	5823.46 (333.46) ***	5402.7 (87.3) *	5899.68 (409.68) ****

Note: Absolute errors are in parentheses. The number of * denotes rank number.

*=rank #1, **=rank #2, ***=rank #3 and ****=rank #4.

Table 6-4: Comparison of Prediction Results (Tire Cord T4 Cumulative Sales in 1977-1979)

Year	Actual	NBM	NMB	NMG	NML
1977	2155	1777.57 (377.43) ****	2423.62 (268.62) **	2296.64 (141.64) *	2497.84 (342.84) ***
1978	2408	2009.41 (398.59) **	2885.17 (477.17) ***	2635.45 (227.45) *	3008.91 (600.91) ****
1979	2635	2263.47 (371.53) **	3385.62 (750.62) ***	2981.77 (346.77) *	3564.99 (929.99) ****

Tables 6-1 and 6-2 show the comparison of prediction results (DRAM 1M and 4M cumulative sale in 1993). From the rank column of these Tables, we can find that NMG is in rank number one on DRAM 4M (1993), Tire Cord T3 and T4 (1977 to 1979) cumulative sale forecasting. This result suggests that this model has better predictive ability than other tested models on DRAM and Tire Cord product sales. It is worth pointing out that NMG's forecasting is very accurate. The absolute errors of DRAM 1M and 4M are 3.89% and 0.41% respectively (see figure 6-1 and 6-2). In addition, the absolute errors of Tire Cord T3 (1977 to 1979) are even lower than 1.59% (see figure 6-3).

Tables 5-21, 5-28 and 5-29 present the forecasting results of the Brockhoff Model. As we can see forecasting results of TS4 are much better than that of TS3, since the sales of Nylon (T3) increase instead of decline from 1977 to 1979. Nevertheless, the prediction

Figure 6-1
Comparison Forecasting Error (%)
for DRAM 1M (1993)

Figure 6-2
Comparison Forecasting Error (%)
for DRAM 4M (1993)

for D5, TS3 and TS4 are successful, because the most points of actual sale are within 95% confidence interval band. Since the Brockhoff Model deals with non-cumulative sales data instead of cumulative sales data, the forecasting results are not compared to the other models.

It is necessary to point out that the NML should be avoided for DRAM and Tire Cord products forecasting even though it fits the data sets well. The model fits the historical data well but has poor forecasting ability. It may be just an example of a method that provides model fit but is not the best forecasting model (Fildes et al. 1983; Makridakis et al. 1984).

6.3 Conclusion

The results of this study provide empirical evidence that the new model (NMG) has better predictive ability even using relatively fewer observations. Figures 6-1 and 6-2 illustrate that NMG and NBM has relatively small forecasting errors on DRAMs. For the forecasting of Tire Cord (T3 and T4) data, NMG also give the best predictive results (see Figures 6-3 and 6-4).

The Brockhoff (1967) and Kumar (1996) models require more parameters to be estimated, so they may be applicable to larger data sets. When the NMB is employed to DRAM products, we find that the parameters p and q , which are parameters of growth rate, change against product generation. Furthermore, while p , the coefficient of innovation, increased, the value of parameter q , the coefficient of imitation, decreased. These two

Comparison Forecasting Error (%)
for Tire Cord T3 (1977-1979)

Figure 6-4
Comparison Forecasting Error (%)
for Tire Cord T4 (1977-1979)

patterns are illustrated in Figures 5-2 and 5-3. These trends can be explained by the fact that has more of an effect on the latest generation of innovation.

Chapter 7

Limitations and Future Research

7.1 Limitations of Study

There are four limitations in this study. The first limitation applies to the generalizability of the findings. Only one high-tech product, DRAM family, and one industry product, Tire Cord textiles were employed in this thesis. Thus, the results apply to the area of DRAM and Tire Cord fabric products. Testing other new product data is necessary to make a reasonable generalization.

The second limitation lies in the collection of other variable data such as price, advertising and promotion data. In this study, we assumed price, advertising and promotion influences were constant in order to examine the effect of the driving force of innovators and imitators in isolation. In fact, those variables may contribute to the rate of diffusion and substitution.

The last limitation is, from a forecasting technique point of view, that holding out data for the latest few periods provides a convincing test but it also halts the most relevant data from being used in the forecast.

The fourth limitation is that the estimation process used requires knowledge of the maximum amount. The normalized form of the growth equation was used in every case to

estimate the parameters. This means that the results of this study are limited to selections in which the maximum amount is known.

7.2 Future Research

In order to encourage further research in this field, the future research suggestions are given in this section. To overcome the limitations that relate to the generalization deficiencies mentioned in last section, more data sets, which may include different product categories, need to be employed to test forecasting models.

With entry to large databases, variables such as price, advertising and promotion of new products should be put into forecasting model to test whether those variables exist and have significant effect on predictive accuracy.

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APPENDICES

Appendix A: Forecasting Accuracy of The Norton and Bass Model (1987) for DRAMs (1985-1987)

The Norton and Bass Model (1987) was used to supply some forecasts based on the DRAM data which was provided by Dataquest. The data comprise 44 quarterly observations of DRAM shipments from 1974 through 1984. In order to examine the forecasting, Norton and Bass forecast quarterly shipments of 16k, 64k and 256k DRAM for three years starting with the first quarter of 1985. To compare the forecasting results with actual sales data which is collected from ICE, the quarterly data is aggregated to annual sales data in this study.

Table A-1: Forecasting Accuracy of 16k DRAM (millions)

Year	Actual	Forecasting	Error	Error %
1985	35	54	-19	-54.29
1986	10	15	-5	-50
1987	**	3.7	**	**

** The data is not available.

Table A-2: Forecasting Accuracy of 64k DRAM (millions)

Year	Actual	Forecasting	Error	Error %
1985	500	1315	-815	-163
1986	380	1224	-844	-222.11
1987	150	734	-584	-389.33

Table A-3: Forecasting Accuracy of 256k DRAM (millions)

Year	Actual	Forecasting	Error	Error %
1985	240	289	-49	-20.42
1986	520	1109	-589	-113.27
1987	680	2638	-1958	-287.94

Tables A-1 to A-3 show that Norton and Bass model (1987) provides a poor forecasting to DRAM products (1985 to 1987).

Appendix B: The Sample of SAS Program for Testing the Norton and Bass Model

(1987)

```
DATA SASUSER.DRAM17;

INFILE 'DCUM929';

INPUT C4K C16K C64K C256K C1M C4M X Y Z U V W;

IF X=19 THEN DELETE;

CARDS;

;

RUN;

PROC PRINT DATA=SASUSER.DRAM17;

PROC SYSNLIN 3SLS DATA=SASUSER.DRAM17 OUTEST=C;

C4K=((1-EXP(-(P+Q)*X))/(1+(Q/P)*EXP(-(P+Q)*X)))*M1*(1-((1-EXP(-(P+Q)*Y))/(1+(Q/P)*EXP(-(P+Q)*Y))));

C16K=((1-EXP(-(P+Q)*Y))/(1+(Q/P)*EXP(-(P+Q)*Y)))*(M2+((1-EXP(-(P+Q)*X))/(1+(Q/P)*EXP(-(P+Q)*X)))*M1*(1-((1-EXP(-(P+Q)*Z))/(1+(Q/P)*EXP(-(P+Q)*Z))));

C64K=((1-EXP(-(P+Q)*Z))/(1+(Q/P)*EXP(-(P+Q)*Z)))*(M3+((1-EXP(-(P+Q)*Y))/(1+(Q/P)*EXP(-(P+Q)*Y)))*(M2+((1-EXP(-(P+Q)*X))/(1+(Q/P)*EXP(-(P+Q)*X)))*M1*(1-((1-EXP(-(P+Q)*U))/(1+(Q/P)*EXP(-(P+Q)*U))));

C256K=((1-EXP(-(P+Q)*U))/(1+(Q/P)*EXP(-(P+Q)*U)))*(M4+((1-EXP(-(P+Q)*X))/(1+(Q/P)*EXP(-(P+Q)*X)))*M1*(1-((1-EXP(-(P+Q)*Y))/(1+(Q/P)*EXP(-(P+Q)*Y)))*M2+((1-EXP(-(P+Q)*Z))/(1+(Q/P)*EXP(-(P+Q)*Z)))*M3+((1-EXP(-(P+Q)*U))/(1+(Q/P)*EXP(-(P+Q)*U)))*M4);
```

$$\frac{(P+Q)*Z)}{(1+(Q/P)*EXP(-(P+Q)*Z)))*(M3+((1-EXP(-(P+Q)*Y))/(1+(Q/P)*EXP(-(P+Q)*Y)))*(M2+((1-EXP(-(P+Q)*X))/(1+(Q/P)*EXP(-(P+Q)*X))*M1)));$$

ENDO C4K C16K C64K C256K;

EXO X Y Z U;

PARMS M1 300 M2 1000 M3 2000 M4 5000 P .01 Q .30 ;

INSTRUMENTS INST1 - INST6;

INST1=X;

INST2=Y;

INST3=Z;

INST4=U;

INST5=U*Z;

INST6=Y*Z;

PROC PRINT;

RUN;

Appendix C: The Sample of SAS Program for Testing the New Model Based on Bass Model (NMB)

```

TITLE ' NEW MODEL BASED ON BASS MODEL';

DATA DRAM814;

INFILE 'DCUM929';

INPUT C4K C16K C64K C256K C1M C4M X Y Z U V W ;

IF Z=0 OR Z>12 THEN DELETE;

F64K=C64K/2645;

CARDS;

RUN;

PROC PRINT DATA=DRAM814;

PROC SYSNLIN DATA=DRAM814 OUTEST=C;

EXO Z;


$$F64K = (1 - \exp(-(P64K + Q64K) * Z)) / (1 + (Q64K / P64K) * \exp(-(P64K + Q64K) * Z));$$


FIT F64K START=(P64K 0.01 Q64K 1) ;

PROC PRINT;

RUN;

```

Appendix D: The Sample of SAS Program for Forecasting of DRAM 1M (1993) with 95% confidence interval using the Norton and Bass Model

```

TITLE 'J_BASED ON BASS MODEL FOR C1M';

DATA DLAST1M;

INFILE 'C:\SAS611\THESIS\NB_DCUM.DAT';

INPUT C4K C16K C64K C256K C1M C4M V W X Y Z U ;

IF C1M=0 THEN DELETE ;

CARDS;

RUN;

PROC PRINT DATA=DLAST1M; RUN;

PROC NLIN DATA=DLAST1M ;

PARMS P=0.0093406928 Q=0.4764399 ;

MODEL C1M=((1-EXP(-(P+Q)*Z))/(1+(Q/P)*EXP(-(P+Q)*Z)))*5892;

DER.Z= ((1/(1+(Q/P)*EXP(-(P+Q)*Z))))**2*((1+(Q/P)*EXP(-(P+Q)*Z))*((P+Q)
*EXP(-(P+Q)*Z))-(1-EXP(-(P+Q)*Z))*(-(P+Q)*(Q/P)*EXP(-(P+Q)*Z)));

OUTPUT OUT=MYOUT1M P=YHAT R=YRESIC L95=CI95L U95=CI95U ;

RUN;

PROC PRINT DATA=MYOUT1M ;

RUN ;

```

Appendix E: The Integration of Equation 2.5

$$dy/dt = -a y \ln(y/b)$$

$$\text{let } y=e^x$$

$$\text{then } dy = e^x dx$$

Substituting.

$$e^x(dx/dt) = -ae^x(x-\ln b)$$

The e^x on both sides cancel. so

$$dx/dt = -a(x-\ln b)$$

$$dx/(x-\ln b) = -adt$$

integrate:

$$\ln|x-\ln b| = -at+c$$

If $y > b$

$$x-\ln b = e^{-at+c}$$

$$x-\ln b = de^{-at}$$

$$x = de^{-at} + \ln b$$

backsubstitute:

$$y = e^{de^{-at} + \ln b} = be^{(de^{-at})}, \quad d > 0$$

The above is a decay curve equation

If $y < b$.

$$x-\ln b = -e^{-at+c}$$

$$x = \ln b - e^{-at+c} \Rightarrow -de^{-at}$$

backsubstitute:

$$y = be^{-de^{-at}}$$

The above equation is a growth curve equation

IMAGE EVALUATION TEST TARGET (QA-3)

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