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MENG ZHAO

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Roger J. Calantone
Major Professor's Signature

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THREE ASPECTS OF NEW PRODUCT LAUNCHES

By

Meng Zhao

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ABSTRACT

THREE ASPECTS OF NEW PRODUCT LAUNCHES

BY

Meng Zhao

The dissertation consists of three separate but related essays, each of which deals with a specific aspect of new product launches. The In the first essay, new product diffusion processes in the presence of market heterogeneities is investigated. Specifically, the roles of network heterogeneities (structural heterogeneity and relationship heterogeneity) are examined by using an agent-based modeling approach. In the second essay, the dynamics of new product launch policies (such as pricing, advertising and promotion, distribution channel, production and inventory management) are investigated through a proposed theoretical framework. The framework integrates various launch polices across the entire supply chain based on the separate resource commitments demanded by individual supply chain elements. In the third essay, the wealth effects (i.e., the stock market's reactions) of innovation announcements, product announcements, and product launches are investigated, using both an event study and an econometrics modeling approach.

Dedication

To my beautiful wife, Liu Wei.

She gives me strength and happiness, and makes my life worth living.

ACKNOWLEDGEMENT

I would like to express my gratitude to my advisor and dissertation chair, Dr. Roger Calantone, for his support, patience, and encouragement throughout my Ph.D. study. He was the reason that I found academic research can be both fun and challenging. His insights and advice were essential to the completion of this dissertation. I will always be indebted to my dissertation co-chair, Dr. Cornelia Dröge, who has embraced me with open arms since I first came to the program. She had provided invaluable support to me through the ups and downs during my Ph.D. study, which I will forever remember. I would like to thank my dissertation committee member, Dr. Ralph Levine, who led me to the field of system dynamics, and Dr. Jun-Koo Kang, who was willing to work with me on the dissertation while he was on his sabbatical leave.

Last, I would like to thank my wife, Wei Liu, her support and encouragement was in the end what made this dissertation possible.

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CHAPTER 1
INTRODUCTION

This dissertation consists of four chapters. Chapter 1 is an overview that provides a brief background of the dissertation, the research questions, and the methodological basis for the research. Chapter 2, Chapter 3, and Chapter 4 are three separate but related essays, each of which deals with a unique aspect of new product launches (see Table 1-1).

Table 1-1 The Organization of the Dissertation

Chapter	Topics	Research Objectives	Theoretical Perspectives	Methods
1	Introduction			
2	New product diffusion process in the presence of market heterogeneity	Examine sources of market uncertainty: *network heterogeneity*	Complex systems	Agent-based modeling
3	New product launch strategies	Investigate how to manage *market uncertainty*	Resource commitments	System dynamics
4	The wealth effects of innovation announcements, product announcements and new product launches	Investigate how to manage *market uncertainty*	Stock market valuations	Event studies, simultaneou s equation modeling

In Chapter 2, new product diffusion processes in the presence of market heterogeneities are investigated. Specifically, the roles of network heterogeneities (structural heterogeneity and relationship heterogeneity) are examined by using an agent-based modeling approach.

In Chapter 3, the dynamics of new product launch policies (such as pricing, advertising and promotion, distribution channel, production and inventory management) are investigated through a proposed theoretical framework. The framework integrates various launch polices across the entire supply chain based on the separate resource commitments demanded by individual supply chain elements.

In Chapter 4, the wealth effects (i.e., the stock market's reactions) of innovation announcements, product announcements, and product launches are investigated, using both an event study and an econometrics modeling approach.

Background: New Product Launches and Market Uncertainties

Product launch, also called product commercialization, is considered the last stage of the New Product Development (NPD) process (Cooper 1993; Crawford 1983). Consistent with previous research, this dissertation views product launch as incorporating all the activities and decisions necessary to present a new product to its target market and thus to begin generating income from sales (Choffray and Lilien 1984; Yoon and Lilien 1985).

The new product launch stage is the most expensive, most risky, and often most time consuming phase of the overall new product development process. It represents the largest investment in the entire process because of the combination of product and marketing expenditures incurred once a decision to launch is approved (Urban and Hauser 1993). More recent research has shown that product launch activities consume a significant amount of total new product costs, often exceeding the combined expenditures of all previous development (Beard and Easingwood 1996; Calantone and Montoya-Weiss 1993). Product launch is also often the most crucial stage in the new product development process, which largely determines a new product's success or failure (Campbell 1999; Calantone and Di Benedetto 1988; Cooper 1979; Cooper and Kleinschmidt 1988; Maidique and Zirger 1984; Song and Parry 1996). Failure rates of 50% to 57% of all U.S. new product launches are not uncommon (Rangan et al. 1992).

The reason that new product launches are particularly challenging is due to the nature of new products, which are either new to the markets, to the launching firms, or to both. The degree of newness of a new product is directly associated with the market uncertainty and technological uncertainty that the launching firm faces. The technological uncertainty is usually not as a crucial an issue as is the market uncertainty, a topic that has been largely addressed in the earlier stages of the new product development process. Therefore, two of the fundamental issues in the new product launch stage are the following: (1) What are the sources of market uncertainties? (2) How can market uncertainties be managed?

In the first essay, one of the neglected sources of market uncertainty is investigated – network heterogeneity. From a new product diffusion perspective, the essay investigates the role of different network topology (i.e., global network structures) and the role of relational heterogeneity (within social networks) in diffusion processes, and their impacts on market demand.

In the second essay, market uncertainty is dealt with from a resource commitment perspective. It introduces a new concept, product launch scale, which is defined as the resource commitment that a firm makes during product launch. The essay proposes a theoretical framework that integrates various launch polices (such as pricing, advertising and promotion, distribution channel, production and inventory management) across the entire supply chain. Using the theoretical framework, the essay investigates how market uncertainty can be managed through dynamically adjusting various launch policies and their associated resource commitments during product launch processes.

The third essay addresses market uncertainty and its associated financial risks through the wealth effects of new product announcements. It argues that new product announcements can be used as strategic communication tools to maximize the positive stock market reactions to new product and innovation announcements, which can provide a hedge against the potential financial risks of product launches.

Research Questions

In the first essay, three research questions are addressed:

1. What is the role played by the network structural heterogeneity (i.e., global network structures or social network topologies) in the product diffusion process?

2. What is the role played by the network relational heterogeneity in the product diffusion process?

3. What is the role played by the internal heterogeneity in the product diffusion process?

In the second essay, four research questions are addressed:

1. How can various launch tactics/policies across the entire supply chain be integrated?

2. What role does resource commitment/launch scale play in product launches?

3. How can product launches be managed under high market uncertainties?

4. Is a dynamic launch strategy better than a static one? If so, under what conditions?

The third essay addresses six research questions.

1. How can New Product Development (NPD) announcements be classified based on the stages of the NPD projects?

2. What are the determinants of the stock market's reactions toward an NPD announcement and how do they affect the stock market's reactions?

3. What are the differences among different types of NPD announcements regarding their stock markets' reactions?

4. How are three sequential announcements for a single NPD project related to each other, with regard to their stock market's reactions?

5. How can stock market reactions toward an NPD project's announcements be maximized?

Methodological Basis

In the first essay, an agent-based modeling (ABM) approach to studying the innovation diffusion process is taken. The ABM approach describes a system from the perspective of its constituent units. In ABM, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses the situation and makes decisions on the basis on a set of rules. The behavior of the system is the outcome of the repetitive interactions among the agents.

The ABM approach is most useful under the following four conditions: 1) When the interactions between the agents are complex, nonlinear, discontinuous, or discrete; 2) When the space is crucial and the agents' positions are not fixed; 3) When the topology of the interaction is heterogeneous and complex, and/or 4) When the agents exhibit complex behavior, including learning and adaptation (Bonabeau 2002). The ABM approach is particularly suitable to modeling innovation diffusion processes in which aggregated adoption behaviors "emerge" from heterogeneous and complex interactions among "agents" (individuals in the potential population).

In the second essay, in order to clarify the dynamics of launch policies and resource commitments adjustments, a system dynamics modeling approach is taken. This approach is taken because conventional methodologies that often take some piecemeal, static, and linear modeling approaches are not able to effectively deal with these dynamics that are the primary interests of this study. The system dynamics approach is able to deal with a dynamic complex system that is constantly changing and that is tightly coupled, governed by feedback, is nonlinear, is history-dependent, self-organizing, adaptive, and that is characterized by trade-offs, counterintuitive reasoning, and is policy resistant (Sterman 2001). This approach uses simulations to build virtual or micro-worlds in which researchers and managers can develop decision skills, conduct experiments, and play. A systemic perspective enables managers to make decisions consistent with the long-term best interests of the system as a whole. However, this system is not designed to predict the future, but rather to help in understanding current phenomenon.

In the third essay, secondary data are used to conduct event studies. Secondary data sources CRSP, Compustat, PR Wire, Business Wire, etc. are consulted to identify new product development projects, and the sequential announcements and product launches for each of the projects. Event studies (Brown and Warner 1985) are natural experiments that assess the impact of an event on a firm's market value using expected stock returns as benchmarks. The event (e.g., a company announcement) contains new information, which is then incorporated in the stock price by investors. Unlike previous studies, this study does not focus on the wealth effects of an event per se (i.e., an announcement, or a product launch), but rather on the relationships among a *set* of wealth effects due to the sequential events of a new product project from the innovation announcement, to the product pre-announcement, to the actual product launch. Furthermore, based on a content analysis of the announcements, the study not only considers the firm-specific determinants of the wealth effects, but also the event-specific determinants (i.e., the content characteristics of the event). These relationships are tested with a three-stage simultaneous equation modeling approach.

CHAPTER 2
DIFFUSION PROCESSES IN THE PRESENCE OF MARKET HETEROGENEITY: AN AGENT-BASED MODELING APPROACH

Introduction

The diffusion of innovations refers to the spread of abstract ideas and concepts, technical information, and actual practices within a social system. This spread denotes flow or movement from a source to an adopter, typically via communication and influence (Rogers 1995). As a theory of communications, the diffusion theory's main focus is on communication channels, which are the means by which information about an innovation is transmitted to or within the social system. These communication channels consist of both the mass media and interpersonal communications. Members of a social system have different propensities for relying on mass media or interpersonal channels when seeking information about an innovation.

In this paper, the main focus is on interpersonal communications, which are usually the most important factors in determining the speed and shape of the S-shaped pattern of the diffusion process. Even though the effect of mass media plays an important role at the beginning of the diffusion process, it is the effects of interpersonal communications that largely determine the diffusion processes' later stages. Empirical evidence shows that interpersonal communications underlying social networks account for adoptions of a variety of innovations, from fertility-control methods (Freedman and Takeshita 1969; Rosero-Bixby and Casterline 1994; Rosero-Bixby and Casterline 1993), agricultural practices

(Rogers 1973; Ryan and Gross 1943), new medicines (Coleman et al. 1966), and ethnic self-identity (Hout and Goldstein 1994), to scientific knowledge (Valente and Rogers 1995) and scientific specialties (Michaelson 1993).

The structure of the paper is as follows. First, relevant literature is reviewed and gaps in the previous research are identified. Second, based on the identified research gaps, research objectives for the current study are established. Third, the methodological basis for answering the research objectives is reviewed and discussed. Finally, based on the research objectives, research questions that can be addressed by the proposed methodology are summarized.

Gaps in Previous Literature

The purpose of this section is to review several streams of literature related to the new product diffusion process: 1) classical diffusion models (include both micro- and macro-level models); 2) network diffusion models and 3) network heterogeneities (i.e., heterogeneity and relational heterogeneity). Based on the literature review, several potential gaps and limitations in past research are identified, which form the foundation for the current study.

The Classical Diffusion Models

In the marketing literature, the main impetus underlying diffusion research is the Bass model (1969), which assumes that potential adopters of an innovation are influenced by two means of communication: mass media and word of mouth. Over the years, various extensions of the Bass model have been developed. The Bass model has a very strong track record in fitting historical sales patterns and is simple to understand and apply (Roberts and Lattin 2000). However, a fundamental weakness of the Bass model is its assumption of homogeneity in populations (Tanny and Derzko 1988). Homegeneity implies that at any point in the process, all individuals who are yet to adopt have the same probability of adopting in a given time period, so that differences in individual adoption times are purely stochastic, or conjectural. Such an implication clearly contradicts the notion that markets are fundamentally heterogeneous, meaning that new product adoption involves a deliberate choice decision on the part of the individual, especially in the case of high involvement products (such as consumer durables). Therefore, there are systematic (not random) differences in adoption time across individuals.

In order to address the unrealistic assumption of population homogeneity by aggregated level diffusion models, micro-level diffusion models have been developed. (for reviews, see Chatterjee and Eliashberg 1990; Wedel and Kamakura 2000). These models assume that the product adoption rate of each individual is different and idiosyncratic. Micro-level diffusion models often use classical utility and attitude models from economics (Lancaster 1966) and psychology (Fishbein 1967) and attempt to model changes in expected product utility over time. Discrete-choice theory then provides a method to transform those utilities to probabilities of purchase and hence, expected market share.

However, the micro-level models also have their shortcomings. First, they do not model aggregated adoption behaviors very well. Second and more important, they focus only on heterogeneity of potential adopters' internal characteristics (such as individual preferences, choices, etc.), while neglecting the heterogeneity caused by the social network to which potential adopters are linked and through which interpersonal communications flow.

Network Heterogeneity

In typical micro-level or macro-level diffusion models, a potential adopter is usually assumed to have direct links with all of the individuals in the population, and thus he or she can have interpersonal communication with any other individual. Apparently, this assumption contradicts empirical evidence of diffusion processes within large populations, since an individual does not have direct ties with most of a given population, and he or she can only conduct interpersonal communications with a very small fraction of that population (the exact size of the fraction is defined by the structure of the social network).

Although many scholars agree on the importance of interpersonal communication to the diffusion process, few studies have successfully traced an innovation through a network of social contacts. The lack of data on diffusion within an entire network stems largely from the difficulty of collecting data over a time period long enough for diffusion to occur. As a consequence, most studies have relied on retrospective data, or network analysis, which relies on formal methods of measuring who talks to whom within a community. Recently there have been some efforts to incorporate social network structures in both analytical diffusion models (e.g., Young 2002) and simulation diffusion models (e.g. Goldenberg et al. 2002). However, the network structures in those models are rather simplistic and unrealistic compared to the real-life social networks.

The heterogeneity nature of the interpersonal communication and social networks are critical factors in the diffusion process. In this study, two types of network heterogeneities are addressed: (1) structure heterogeneities that are due to individuals' positions in their social network structures; and (2) relational heterogeneities that are due to different strengths of interpersonal influences through direct ties (Valente 1995).

Structural Heterogeneity

The heterogeneities of network structures in social networks have long been noted by researchers in the field of social network analysis. Social network analysis has traditionally focused on characteristics of small networks and local network structures and patterns, such as centrality, structural balance and transitivity, cohesion, structural equivalence, actor positions, and subgroups (Wasserman and Faust 1994). Both empirical studies (e.g. Harkola 1995), and modeling efforts (e.g. Valente and Davis 1999) have applied these concepts in the innovation diffusion literature. Social network theories have developed multiple measures (e.g., centrality network efficiency) to describe social process such as innovation diffusion processes. However, these theories assume linear models of social processes, such as Markov models of diffusion. Like most other social network analyses, these studies focus on small networks and on the relationship of local structures and individual adoption behaviors. When applied to networks of arbitrary size and structure, the computational costs may be prohibitive, and the benefits are at any rate unclear if the process of interest is inherently nonlinear. There is clearly a lack of research on the overall structures of large social networks characterized by structural heterogeneities and their relationships to aggregated adoption behaviors in diffusion processes. Therefore, this study addresses structural heterogeneity by studying the relationships among the global structures of social networks (that is, different topologies of social networks).

Relational Heterogeneity and Market Segmentation

Since Smith's (1956) introduction of the notion of market segmentation, this topic has become a central concept in both marketing theory and practice. He stated that market segmentation involves viewing a heterogeneous market as a number of smaller homogeneous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction of their varying wants. In the diffusion literature, Roger (1995) divides potential adopters into five market segments: innovators, early adopters, early majority, late majority, and laggards. Building on the research of Coleman, Katz, and Menzel (1966), Midgley et al. (1992) illustrate how different network links between population members can affect the diffusion process and how cliques can lead to different cumulative adoption patterns for the population.

However, past studies tend to segment the market based on internal heterogeneity, that is, the heterogeneity of individuals' adoption thresholds and various factors that affects these thresholds. Such studies neglect the heterogeneity due to the network, particularly the situation in which members of the network can be divided into several groups (segments) based on the heterogeneity of the relationship among members. That is, the strengths of network links between groups are heterogeneous and weak, while the strengths of the network links within the group are strong and homogenous. In addition, the market segmentation literature (innovation diffusion literature in particular), tends to explicitly or implicitly assume that members of the *same* segment are clustered together spatially or relationally, while members from *different* segments can be segregated spatially or relationally. The current research argues that individuals from two different market segments can be completely mixed together spatially, as well as relationally in the social network, while the two segments can nevertheless demonstrate distinctively different diffusion processes. Relational heterogeneity is very well supported and studied at the individual level and at the local structure level in the social network analysis literature (e.g. Granovetter 1973). However, there are very few if any studies that address relational heterogeneity across the entire social network.

Research Objectives

The purpose of this dissertation is to extend the research on new product diffusion by addressing the research limitations previously identified in the foregoing sections of this work. The research objectives include the following imperatives:

1. Model network-based product diffusion dynamics, allowing that each potential adopter makes adoption decisions based upon both unique internal characteristics (i.e. internal heterogeneity) and the unique network environment (i.e., network heterogeneity).

2. Develop a set of network topologies that reflects the real-life characteristics of the large social networks in which most product diffusion processes occur.
3. Model internal heterogeneity.
4. Model network structural heterogeneity based on the proposed network topologies.
5. Model relational heterogeneity.
6. Test the impact of structural and relational heterogeneity on behaviors in product diffusion processes.

Research Questions Addressed

Based on the objectives set forth for this study, the following three research questions are investigated:

1. What is the role played by the network structural heterogeneity (i.e., global network structures or social network topologies) in the product diffusion process?
2. What is the role played by the network relational heterogeneity in the product diffusion process?
3. What is the role played by the internal heterogeneity in the product diffusion process?

Methodological Basis for Answering the Research Objectives

The dissertation makes use of an agent-based modeling approach as the primary means for addressing the research objectives. In this approach, the diffusion dynamics are modeled based on the network threshold model; four different types of network topologies are applied to model the social network structures underlying the diffusion process. The purpose of this section is to review the literature in the four types of social network topologies, the network threshold model, and the agent-based modeling methodology, and explain how the knowledge derived from this review of the literature can be applied in this study.

Social Network Topologies

A social network is a set of people or groups of people ("actors," in the jargon of the field), having some pattern of interaction or "ties" among them. Friendships among a group of individuals, business relationships between companies, and intermarriages between families are all examples of networks that have been studied in the past. Typically, network studies in sociology have been data-oriented, involving empirical investigation of real-world networks, followed usually by graph theoretical analysis aimed at determining the centrality of influence of the various actors. However, the innovation diffusion process often involves thousands, even millions, of potential adopters, which make the empirical mapping of the social network unfeasible. Therefore, researchers often use hypothetical network structures based on some of the network topologies that are believed to have characteristics similar to the real-world networks.

Network topology refers to the shape or layout of a network, or the network's layout, that is, the specific physical or logical arrangement of the elements of a network. How different nodes in a network are connected to each other and how they communicate are determined by the network's topology. In network terminology, nodes are called *vertices*, while links are called *edges*. In order to generate network structures that mimic the real-world social network, it is necessary first to address the question "What are the properties of a social network?"

In a literature review regarding the latest developments in social network topology, Newman (Newman 2000) observes that real-world social networks have three key properties. First, the diameter of the social network (that is, the average number of edges between any pair of vertices has to be small, even when the social network itself is very large. This is the famous "small-world" property of social networks (Milgram 1967; Pool and Kochen 1978): any two individuals selected randomly from almost anywhere on the planet are "connected" via a chain of no more than six intermediate acquaintances (a notion made popular by the Broadway play and later the movie, "Six Degrees of Separation".) (Guare 1990). Second, in the social network, a person's friends are more likely also to be friends of each other. This property is called *clustering*, which can be measured by a clustering coefficient, which is defined as the average fraction of pairs of neighbors of a vertex, which are also neighbors of each other. Third, the distributions of a vertex's number of edges is highly skewed, with a small number of vertices having an unusually large number of edges. This follows a power-law distribution. (Do you need to briefly define a power-law distribution here?)

The Random Network

The random network topology was proposed by Erdö and Réyi (1959). It is the most extensively studied network topology. The random network can be defined as follows: a number N of vertices are connected by edges, such that each pair of vertices (e.g. i, j) has a connecting edge with independent probability p. Random networks have been used to model social networks in quite a few diffusion studies, such as Valente (1999). In a random network, if the average number of edges per vertex is z, a vertex has z neighbors, z^2 second neighbors, z^3 third neighbors, and so on. Therefore, the diameters of the random networks are rather small compared with the size of the networks themselves ($D = \log N/\log z$), a circumstance which meets one of the characteristics of social networks. However, a significant problem exists with using the random network as a model of social networks. The problem is that the clustering coefficient of the random network is very small when the network is large ($c = z/N$). Therefore, in a random network, a friend's friends are *not* more likely to be friends. The distribution of edges follows a Poisson distribution, which is quite different from the power-law distribution.

Two-Dimension Lattice (Cellular Automata Network)

A two-dimension lattice is a cell in a two dimensional grid. A vertex in two dimensions can be defined as having 4 neighbors, or 8 neighbors, or more. This type of network structure is also called cellular automata, which is used quite often in innovation diffusion studies (e.g. Goldenberg et al. 2002). The advantage of the cellular network is that it provides a pseudospatial structure for interacting agents. It also has a high clustering property. However, a 2-dimension lattice does not have the remaining two properties of a social network. First, its diameter is rather large, proportional to the Network size N. Second, it has a constant number of edges for each of its vertices.

Watts and Strogatz's (1998) Small-World Network

Unlike the two dimensional lattices and the random networks, many real-world networks of interactions appear simultaneously to possess properties both of random graphs and of regular lattices. Watts and Strogatz (1998) propose a network model that interpolates between these two extremes by taking a regular lattice and randomly "rewiring" some of its edges. The resulting graphs are characterized by a high degree of local clustering (like regular lattices), but also possess the short vertex-vertex distances similar to those found in random graphs (even for quite small densities of rewired edges). These "small-world" networks, named after the small-world phenomenon of sociology, provide a model for the topology of a wide variety of systems, such as the Internet, power grids, patterns of neuron connectivity, networks of movie actors (Watts1999), and the owner network of German firms (Kogut and Walker 2001)

Watts and Strogatz's small world network can be constructed as follows. Starting from a ring lattice with n vertices and k edges per vertex, each edge is rewired at random with probability p[1]. This construction produces graphs between regularity (p=0) and disorder (p=1), and thereby probing the intermediate region 0< p <1. As p increases, the network diameter L(p) drops

[1] In this study, p is set to 0.1 for all the small-world network structures.

rapidly, while the clustering coefficient C(p) remains almost constant. This implies that the transition to a small world is almost undetectable at the local level.

An automata network is highly clustered and the characteristic path length is large, scaling with the typical linear dimension of the network. On the other hand, a completely random network is poorly clustered and the characteristic path length is short, scaling logarithmically with the size of the network. Watts and Strogatz (1998) show that by shifting gradually from a regular network to a random network, the path length and clustering changes differently. The characteristic path length drops quickly, whereas the amount of clustering drops rather slowly. Therefore, it only takes a small number of short cuts between cliques to turn a large world into a small world, while not reducing much of the clustering coefficient.

Barabási and Albert's (1999) Power-Law Distribution Network

One social network property that Watts and Strogatz's small world network does not demonstrate is the power law distribution of the number of edges that a vertex in the network has. A great deal of empirical evidence shows that many real-world networks such as the WWW (Barabási and Albert 1999), the Internet (Faloutsos et al. 1999), the U.S. power grid (Aiello et al. 2000), the research citation network, and networks of movie actors follow a power law distribution. In a power law distribution, the fraction of nodes with degree d is proportional to $1/d^{\alpha}$ for some constant $\alpha \geq 0$.

The power law distribution does not have a peak. Rather, a histogram following a power law is a continuously decreasing curve, which implies that many small events coexist with a few large events. The power law mathematically formulates the fact that in most real networks, the majority of nodes have only a few links and that the numerous tiny nodes coexist with a few big hubs (i.e., nodes with an anomalously high number of links) (Barabasi 2002). Various algorithms to generate power-law network have been proposed, such as Xulvi-Brunet and Sokolov (2002), Newman et al. (2001), Aiello et al. (2001), etc. In this study, Barabási and Albert's (1999) original algorism is used to generate the power-law network. The specification of the algorithm is as follows:

Start with a small number m_0 of vertices. At every time step, create a new vertex with m_0 edges linking the new vertex to $m(>m_0)$ different vertices already present in the system. To incorporate preferential attachment, assume that the probability p that a new vertex is connected to vertex i depends on the connectivity k of that vertex, so that $p(k_i) = k_i/\Sigma_j k_j$. After t time steps, the model leads to a random network with $t+m_0$ vertices and mt edges.

The Network Threshold Model

The Threshold model was first proposed by Granovetter (1978) to model collective behaviors. Applying it to the diffusion process, Valente (1995) proposes that a threshold should be conceptualized as the proportion of an individual's network that needs to adopt a behavior before that individual would normally do so. Individuals have different thresholds for adoption of an innovation. The threshold model does not determine how these thresholds are obtained. That is, it avoids determining the socio-psychological determinants of an individual's threshold. Considerable empirical support for threshold models have been found in a wide range of fields, such as epidemiology, geography, markets and economies, collective behaviors, interaction communication technologies, public opinion, decay processes, and subgroups (Valente 1995).

However, Valente (1995) shows that when the proportion of an individual's network neighbors who have adopted a new product has exceeded that individual's threshold, he or she does not necessarily adopt the product immediately. Instead, there can be a lag between the point in time when the individual's exposure reaches the threshold and the time of adoption. The magnitude of this threshold lag indicates the degree of delay in threshold activation, which is due to disincentives, for example such as high product costs and positive inducements such as rebates. Empirical evidence shows that threshold lag has a skewed distribution, with more individuals having shorter rather than longer lags (e.g. the threshold lags for Korean family planning village (Valente 1995). As such, the time lag distribution can be modeled as a geometric distribution.

The Agent-Based Modeling Approach

In the current study, an agent-based modeling (ABM) approach to studying the innovation diffusion process is taken. The ABM approach describes a system from the perspective of its constituent units. In ABM, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses the situation and makes decisions on the basis on a set of rules. The behavior of the system is the outcome of the repetitive interactions among the agents. The ABM approach is most useful under the following conditions: 1) when the interactions between the agents are complex, nonlinear, discontinuous, or discrete; 2) when the space is crucial and the agents' positions are not fixed; 3) when the topology of the interaction is heterogeneous and complex, and/or 4) when the agents exhibit complex behavior, including learning and adaptation (Bonabeau 2002). The ABM approach is particularly suitable to modeling innovation diffusion processes, in which aggregated adoption behaviors "emerge" from heterogeneous and complex interactions among "agents" (individuals in the potential population).

In the agent-based modeling approach, each agent is allowed to assume a heterogeneous adoption threshold (internal heterogeneity) and a heterogeneous local network structure, which is determined by the global structure of the social network (i.e., structural heterogeneity). The relational heterogeneity can be modeled by allowing heterogeneous strengths of the interactions (i.e., interpersonal communications) across different market segments.

The Simulation Models

The Implementation of the Network Structures

In the previous section, the algorithms to generate the four types of network structures are discussed. In order to make meaningful comparisons among the four types of network structures in the simulation models, the four types of network structures are all generated with n = 1600 nodes and an average number of links per node $\bar{v} = 24$, a method which has the following implications:

1. **Automata Network:** The number of links for each agent is fixed at 24 without any variation.

2. **Random Network and Small-World Network:** The probability for any of the two nodes having direct links is p = 1/12 = 0.833, and v follows a Poisson distribution[2].

3. **Power-Law Network:** The probability for any of the two nodes having a direct link is p = 0.833 and v follows a Power-Law distribution.

The Basic Model

In the basic simulation model, there are 1600 agents that are linked together based on one of the four network structures discussed in the methodology section. Among these agents, 50 agents are randomly selected and assigned as innovators (i.e, those who have adopted the products at the earliest stage of new product/innovation introduction) at the beginning of the simulation. All other agents are potential innovator adopters with the same adoption threshold (several levels of adoption threshold are used, depending on the experiment condition.) After the simulation starts, the following steps are executed repeatedly in the simulation until the end of the simulation:

Step1: An agent is randomly selected and activated.

Step2: If the agent is an adopter, then bypass Step 3.

[2] The exact Poisson distributions for small-world networks and random networks are not the same, even though their average numbers of links per node are the same. This is because the distributions of the small world networks are also dependent on how many "random links" there are within the small-world networks. (In this model, the percentage of random links is set to 10 percent).

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Step3: The agent examines the statuses of its immediate neighbors (which is defined as those agents who have direct network links with the focal agent). If the percentage of the adopters in the agent's neighborhood exceeds the adoption threshold, then the agent becomes an adopter itself with an adoption probability of 0.5[3]; otherwise, the agent remains as a non-adopter.

Step 4: If all the agents in the model become adopters, or if the model reaches equilibrium[4], then the simulation stops; otherwise, go to Step 1.

The Two-Segment Model

In the two-segment model, relational heterogeneity is assumed. That is, the agents in the model belong to two market segments, and the agents from the two segments are mixed together within the social network. Following the literature (such as Rogers 1995, Goldenberg, et al. 2002), only one market segment is embedded with innovators and is defined as the innovator segment; the other segment is defined as the follower segment. Like the basic model, the two-segment model contains 1600 agents that are linked based on one of the four types of network structures. However, these 1600 agents are randomly divided into two segments. The exact size of the innovator segment is chosen according to experiment conditions. Within the innovator segment, 50 innovators

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[3] The adoption probability models the diffusion delays due to factors other that peer pressure (i.e, adoption threshold), such as the limits of an agent's income, decision time, etc. Valenti (1995) suggested that the diffusion delays can be modeled as a stochastic process with a geometric distribution.

[4] The equilibrium is defined as a situation when none of the non-adopters have enough adopters in their respective neighborhoods to exceed the adoption threshold. Operationally, it is assumed that an equilibrium is reached when a simulation runs more than 20,000 consecutive rounds (a repeat of Step 1 to 4 is counted as one round) without any new adopters. The chance for error is rather small: $(1-1/1600)^{20000} \approx 0.000004$.

are randomly selected. After the simulation starts, the following steps are executed in the simulation repeatedly until the end of the simulation.

Step1: An agent is randomly selected and activated.

Step2: If the agent is an adopter, then bypass Step 3.

Step3: The agent examines the statuses of its immediate neighbors. A weighted percentage of adopters in the agent's neighborhood is calculated. In the calculation, a neighbor from the focal agent's market segment is weighted 1.0, while a neighbor *not* from the focal agent's market segment is weighted as 0.3[5]. If the weighted adopter percentage exceeds the adoption threshold, then the agent becomes an adopter itself with an adoption probability of 0.5; otherwise, it remains as a non-adopter.

Step 4: If all the agents in the model become adopters, or if the model reaches equilibrium, then the simulation stops; otherwise, go to Step 1.

The Research Design

In order to address the research questions proposed in this study, the effects of three variables in new product diffusion processes are examined (See Table 2-1). These variables are the adoption threshold, network structures, and network heterogeneity (in the two-segment model). Therefore, simulation experiments are conducted based on various experimental conditions of the three variables. In the basic model, five levels of adoption thresholds (i.e., 0.1, 0.3, 0.5, 0.7, and 0.9) and four types of network structures are tested (i.e., 5 x 4 = 20 experiment conditions). In the two-segment model, four levels of innovators

[5] The different weights models the fact that social network links (or word-of-mouth effects) between agents from different market segments are weighted less than those from the same market segment.

segment sizes (10%, 30%, 50%, and 70%), and four types of network structures are tested (i.e., 4 x 4 = 16 experiment conditions). The adoption threshold is fixed at 0.1 in the two-segment model.

Table 2-1 Research Design

			Network Structures			
			Random Network	Automata Network	Small World Network	Power-Law Network
Single Segment Mode	Adoption Threshold	0.01				
		0.05				
		0.10				
		0.15				
		0.20				
Two Segment Model	The Innovator Segment's Relative Size	10%				
		30%				
		50%				
		70%				

For each experimental condition, 100 replications of the computer simulation are conducted with different random seeds. The random seeds are generated based on the machine's time at the start of each replication, which further ensures the pseudo-randomness of the simulations.

The Simulation Results

The Results of the Single-Segment Model

Diffusion cascade is defined as a diffusion process in which the entire population has adopted an innovation. Diffusion cascade does not always occur. The simulation results (see Table 2-2) show that the likelihood of diffusion cascades decreases as the adoption threshold increases. This result is not surprising, because a higher adopter threshold implies higher difficulties in

spreading the innovation among the adoption, which, in turn, reduces the likelihood of diffusion cascades.

Table 2-2 The Likelihood of Adoption Cascade

Network Topologies	Threshold Levels	% of Diffusion Cascade
Random Network	0.01	100%
	0.05	100%
	0.1	100%
	0.15	93%
	0.2	0%
Automata Network	0.01	100%
	0.05	100%
	0.1	100%
	0.15	93%
	0.2	40%
Small-World Network	0.01	100%
	0.05	100%
	0.1	100%
	0.15	100%
	0.2	47%
Small-World Network	0.01	100%
	0.05	100%
	0.1	100%
	0.15	77%
	0.2	0%
Power-Law Network	0.01	100%
	0.05	100%
	0.1	100%
	0.15	100%
	0.2	30.00%

Finding #1: The adoption threshold negatively affects the likelihood of adoption cascade.

The results in Table 2-2 show that whether a particular diffusion leads to a diffusion cascade is not only determined by agents' adoption thresholds, but also

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by the initial conditions of the simulation (that is, the selection of the random seed, which determines the initial conditions of the simulation, such as innovators' locations, local network structures, the agents' activation sequence, etc.). In addition, it is also found that the diffusion patterns[6] can vary greatly if only the initial conditions are changed. For example, Figure 2-1 shows the fluctuations of the peak time for diffusions with different network structures at an adoption threshold of 0.05. On each vertical line, the highest point and the lowest point show the maximum peak time and the minimum peak time respectively, while the point in the middle indicates the mean of the peak time for diffusion processes at a particular experiment setting. Similar findings are also derived from simulation results for 50 percent penetration time (i.e., the time it takes for 50 percent of the population to become adopters), 80 percent penetration time, and 100 percent penetration time. Based on the above observations from the simulation results, the following statement can be made:

Finding #2: The diffusion process is path dependent. That is, one of the key factors that determine an innovation's diffusion pattern is the initial conditions of the market (such as the initial locations of innovators, their initial local network neighborhood, etc.).

Figures 2-2 through Figure 2-5 demonstrate the adoption threshold's effect on new product diffusion patterns under the four different types of network structures (i.e., Automata Network: Network=1; Random Network: Network=2;

[6] In this study, we examine the diffusion patterns by comparing the time it takes for a diffusion process to reach its peak with regard to 50 percent, 80 percent, and 100 percent of the population.

Small-World Network: Network =3; Power-Law Network: Network = 5)[7]. In each of these aforementioned figures, different colors represent different levels of adoption thresholds used in the simulations (Blue: Threshold=0.01; Black: Threshold:=0.05; Red: Threshold=0.10; Yellow: Threshold=0.15; Green: Threshold=0.20). The y axis indicates the number of new adopters, and the x axis represents the number of the time period in the simulation. Each time a unit is counted as one simulation period. In this study, each time period accounts for 800 simulation rounds (i.e, Step 1 to Step 4). For example, Figure 2-2 shows the diffusion patterns under the automate network structures. The blue line indicates the number of new adopters at each time period during the entire diffusion process when the agents' adoption threshold is 0.01. Meanwhile, the black, red, yellow, and green lines represent thresholds of 0.05, 0.10, 0.15, and 0.20 respectively. It should be noted that the diffusion curves in Figure 2-2 through 2-5 are not the single realization of one simulation run on various experimental conditions. Instead, the diffusion curves represent the averaged results from 100 replications based on the same set of experimental conditions. The results show that regardless of the network structures, as the adoption threshold increases, the diffusion curves become flatter and longer[8]. That is,

Finding #3: The adoption threshold negatively affects the speed of the diffusion[9].

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[7] All the simulation results for each of the experimental settings are aggregated, and an average diffusion pattern for each experiment settings was obtained. In order to make consistent comparisons, only those simulation replications with diffusion cascades have been included.
[8] It has to be noted that the effect of adoption thresholds with automata network are not as significant as with other types of network structures.
[9] The adoption speed is defined as the number of new adopters at each time period.

Finding #4: The adoption threshold negatively affects the variance of diffusion speed.

Figure 2-1 Single Market Diffusion: B...

Figure 2-1 Single Market Diffusion: Peak Time

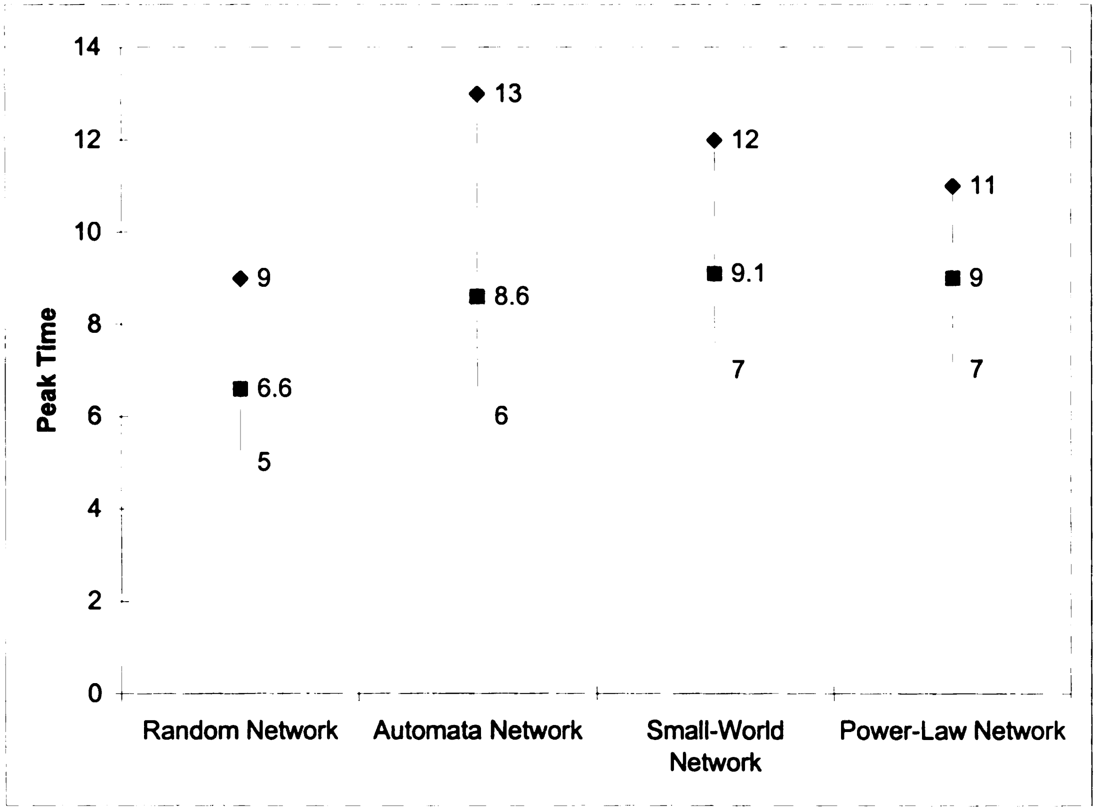


Figure 2-2 Saturated Diff

Figure 2-2 Saturated Diffusion: Single-Segment Diffusion Comparison Across Conditions (a)

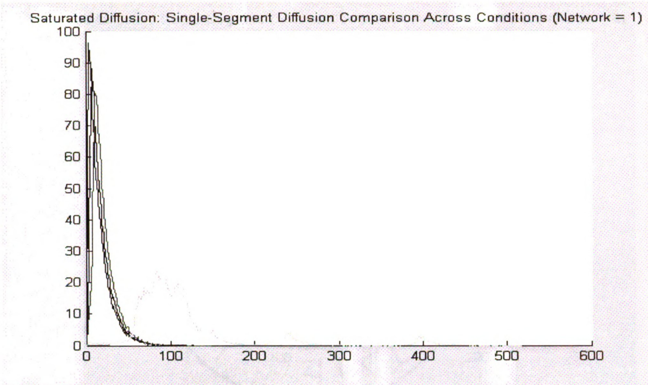


Figure 2-3. Saturated Diff...

Figure 2-3 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (b)

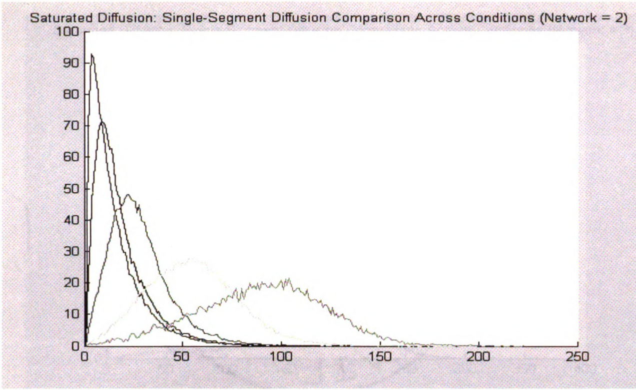


Figure 2-4 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (c)

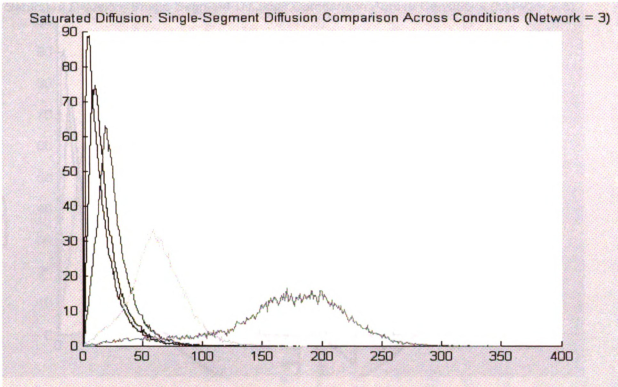
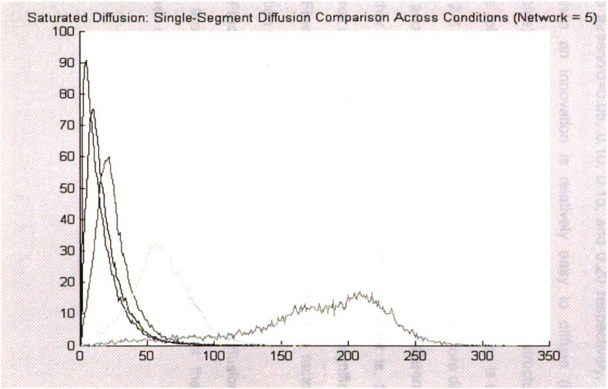


Figure 2-5 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (d)



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Figures 2-6 through Figure 2-9 show the role of network structures (blue: random network; black: automata network; red: small-world network with 10% randomness; yellow: small-world network with 20% randomness; green: power-law network) in the diffusion process. In these figures, condition = 2, 3, 4, and 5 refer to threshold=0.05, 0.10, 0.15, and 0.20 respectively. The results indicate that when an innovation is relatively easy to diffuse (i.e., lower adoption thresholds), the diffusion patterns of different network structure are rather similar and the role of network structures in diffusion processes is less significant (e.g., Figure 2-6 and 2-7). However, when an innovation is more difficult to diffuse (i.e., higher adoption threshold), the diffusion patterns of different network structures are rather different (e.g., Figure 2-8 and 2-9). That is, the role of network structures in diffusion processes becomes much more significant. Therefore,

Finding #5: The network structures are a key factor in determining an innovation diffusion process and its pattern.

Finding #6: The more difficult an innovation diffusion becomes (i.e., the higher the adoption threshold), the more significant the effect of network structures on the diffusion process is.

Figure 2-6 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (e)

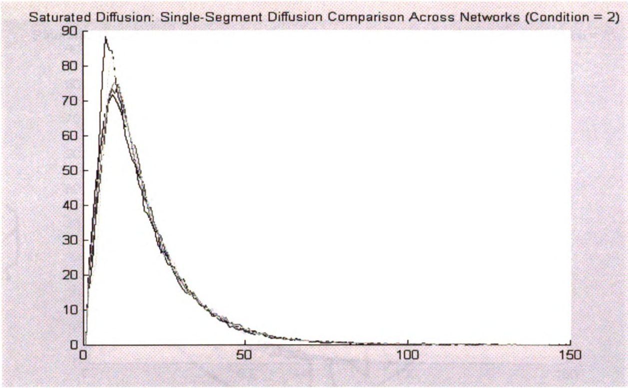


Figure 2-7 Saturated Diffusion

Figure 2-7 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (f)

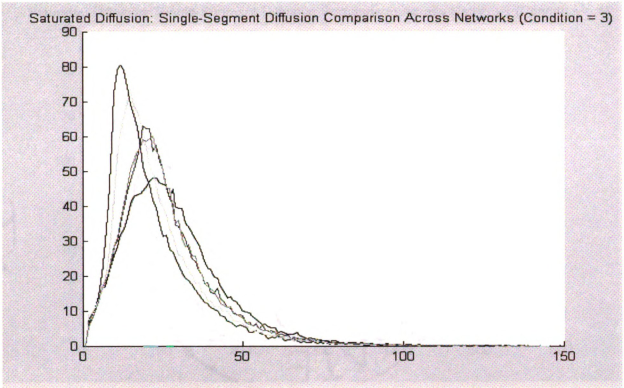


Figure 2-8 **Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (a)**

Figure 2-8 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (g)

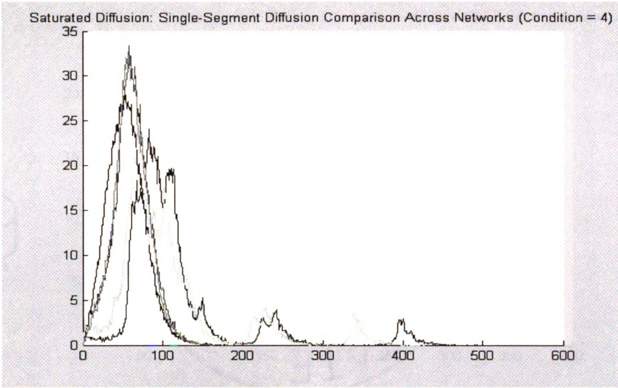
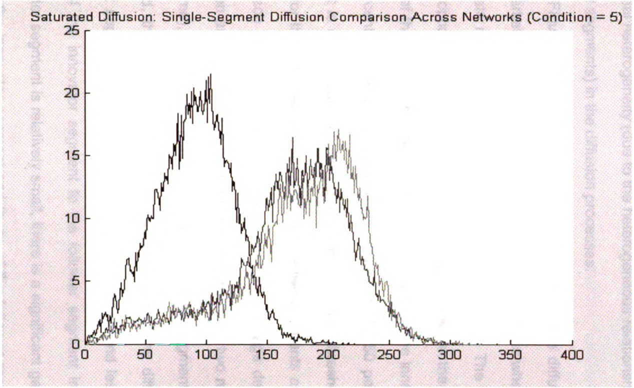


Figure 2-9 **Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (b)**

Figure 2-9 Saturated Diffusion: Single-segment Diffusion Comparison Across Conditions (h)



The Two-Segment Model

The results of the two-segment model support all the key findings of the single-segment model. The two-segment model also investigates the role of the relational heterogeneity (due to the heterogeneous relationships between the two market segments) in the diffusion processes.

Figures 2-10 through 2-12 show the respective diffusion patterns of the two market segments at different market configurations when the network is an automata network and the adoption threshold is 0.10. The blue lines represent the adoption patterns of the innovator segment, while the red lines represent those of the follower segment. The relative sizes of the innovator segemnts are 10 percent (Figure 2-10), 30 percent (Figure 2-11), 50 percent (Figure 2-12). First, it is quite clear that even though the adoption thresholds are exactly the same for the two market segments and the two segments are completely mixed with each other in the social network (i.e., the average degrees of separation between an innovator and potential adopters from the two market segments are the same), the diffusion patterns of the two market segments are very different. Second, the effect of relational heterogeneity (i.e., the differences of the two market segments' diffusion patterns) becomes less and less significant as the ratio of the innovator segment to the follower segment increases. When the innovator segment is relatively small, there is a significant gap between the take-offs of the innovator segment and those of the follower market (i.e., the saddle effect defined by Goldenberg, et al. 2002). When the innovator segment is relatively large, the take-offs and peak times for the innovator segment and

follower segment become very similar. The above observations are also supported with other network structures and different levels of adoption threshold.

Finding #7: The relational heterogeneity is an important factor in determining the diffusion patterns of an innovation. Specifically, the diffusions of an innovator segment and a follower segment behave quite differently, regardless of the adoption thresholds and the distributions of the two market segments in the population.

Finding #8: The saddle effects decreases as the ratio between the size of the innovator segment and follower segment increases.

Figure 2-10 Diffusion Model with Two Segments (a)

Figure 2-10 Diffusion Model with Two Segments (a)

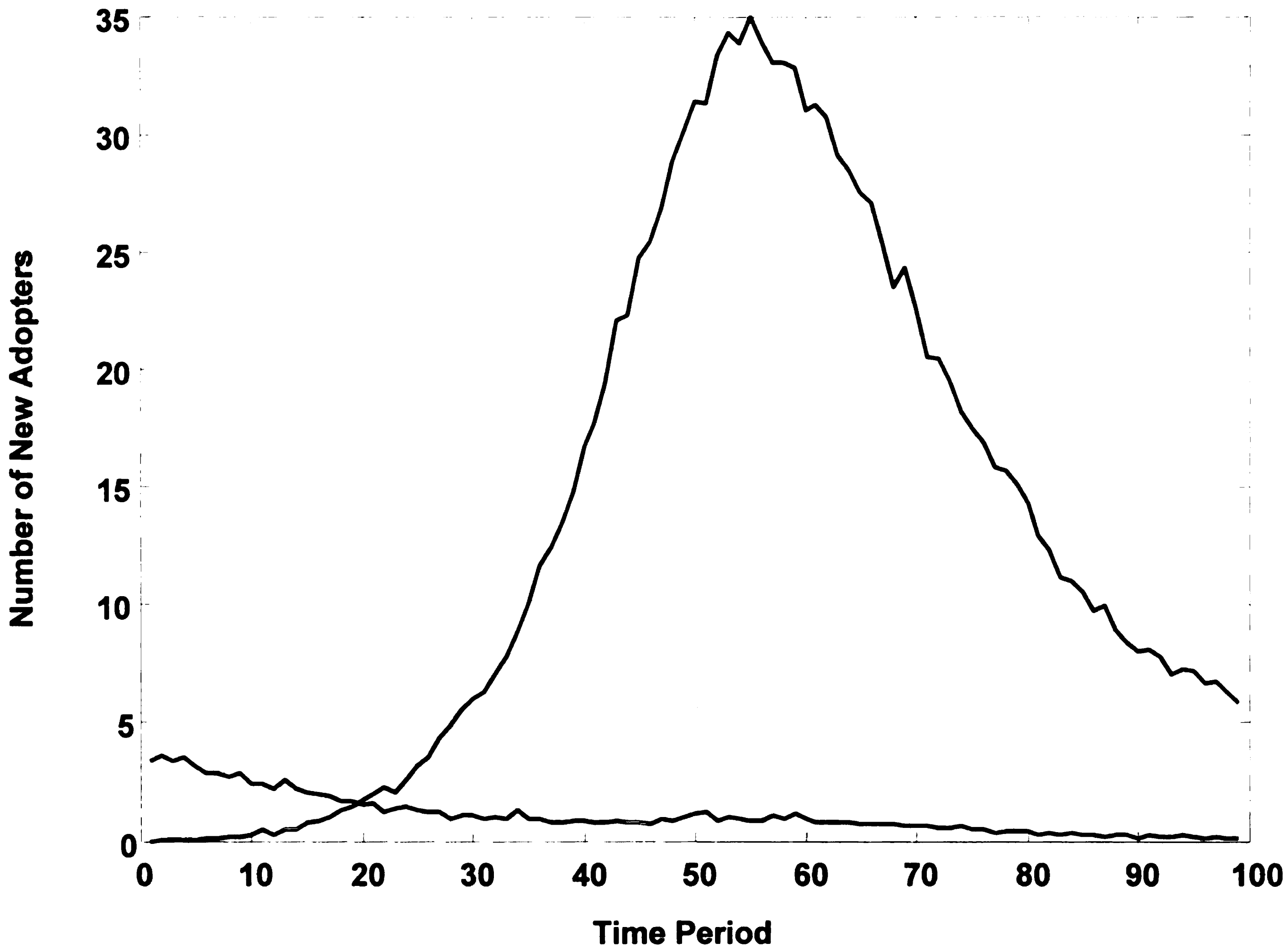


Figure 2-11 Diffusion Model with Two Segments (b)

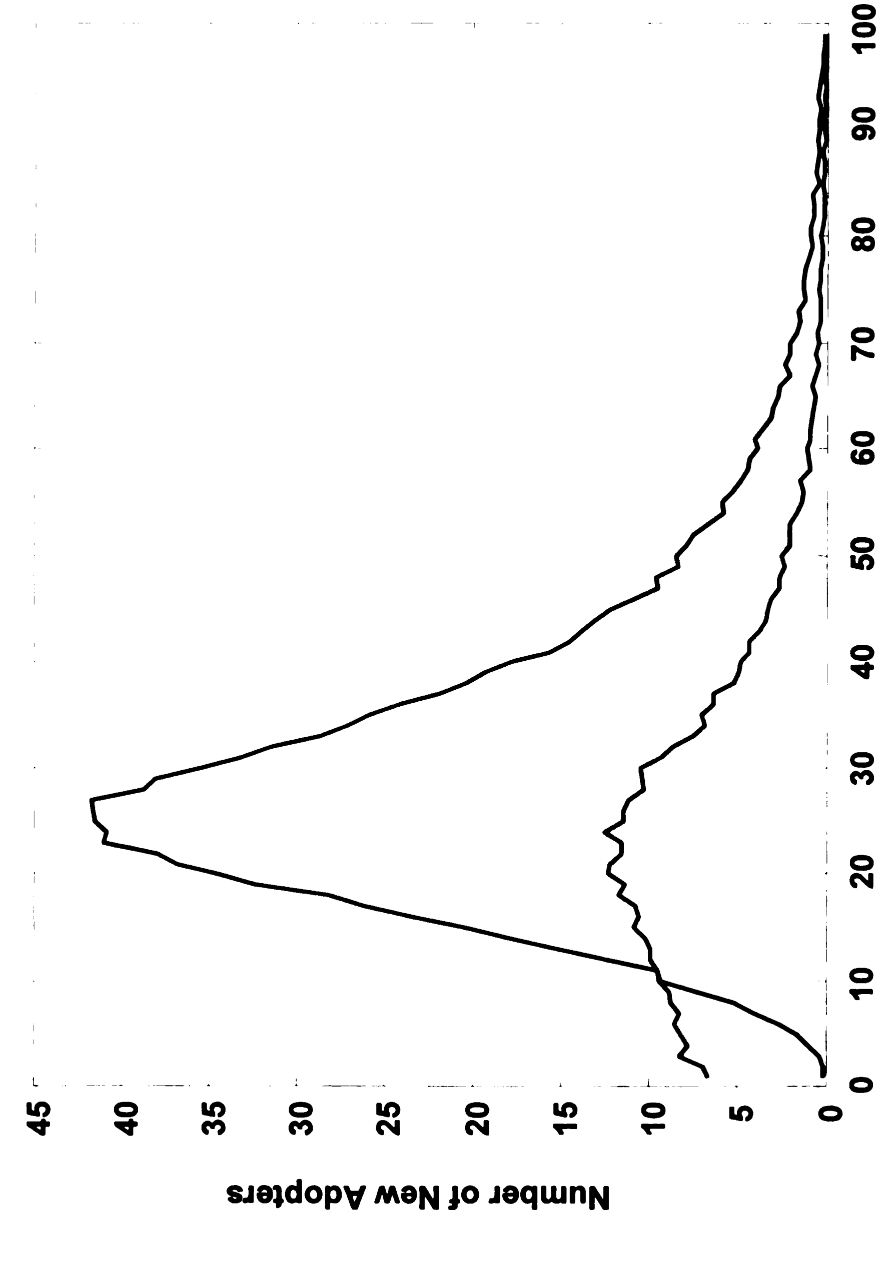
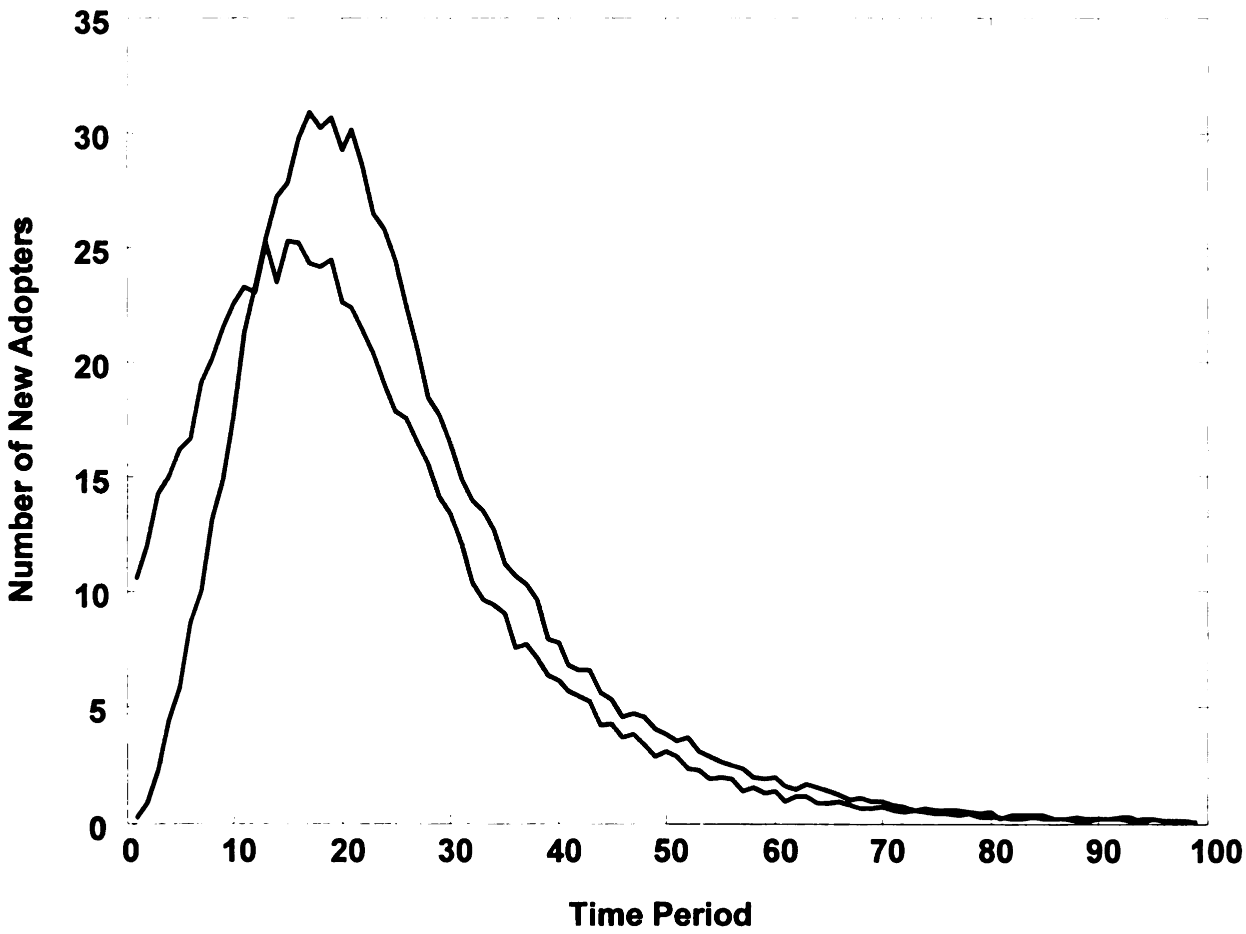


Figure 2-13. Diffusion Mod[illegible]

Figure 2-12 Diffusion Model with Two Segments (c)



Discussion

Granovetter (1978) postulated that in threshold models of collective behavior, an individual engages in a given behavior in proportion to the number of people in the social system already engaging in that particular behavior. Rogers (2003) empirically demonstrates clear segmentation of adopters into (minimal) innovators and followers. We see that expanding the basic postulated model of diffusion through a systematic examination of structural heterogeneity leads to many interesting and in some cases unexpected, insights.

Diffusion is very difficult to predict, especially due to subtle, but sensitive effects of initial conditions, as well as to both endogenous and exogenous heterogeneity.

We also see that network typologies affect diffusion patterns. From a theory-building standpoint, these difficulties can imply that researchers must be especially careful with their choice of network typology in system simulation research. Without such care, artifactual results due to incorrect choices of network typology might occur.

From a substantive view of diffusion theory we also observe that the specific nature (segmental group) of the agent has a vector of interesting implications. Who the agent is (segment membership and identification), where the agent is located relative to other members of various segments, as well as what other agents the focal agent is associated with are all important issues. It is not just who you are, but where you are located and with whom you are associated that makes a difference in diffusion networks. Although such an assertion appears obvious in retrospect, this research provides key corroboration of that assertion. Several past studies used only a cellular automata network to examine diffusion patterns only when a saddle appeared; while a broader perspective such as this researcher's can reveal how such effects vary for different types of networks under various conditions.

Another interesting finding is that relational heterogeneity alone can be used as a basis for market segmentation. Many different individual level aspects are posited as underlying bases for market segments (Wedel and Kamakura 2000). However, external relational factors are, as this research demonstrates, a natural extension of traditional multi-stage market segmentation analysis. This finding extends the relational segmentation of supply chain members and other naturally occurring hierarchical groups. The finding also has implications for multistage segmentation analysis of business units. Moore (1991) as well as Goldenberg, et al. (2002) describe saddle points in acceptance of innovations and increasing difficulty after initial rapid diffusion. Relational targeting can overcome such bottleneck market schemata by recognizing, a priori, the multi-segment switchover inefficiencies of some markets.

Future Research

Future research can easily address some of the remaining questions in network heterogeneity employing the system that this researcher has investigated. The adoption of innovations is inherently complex because the behavior of persons in groups is inherently complex, as are the benefits derived from technological innovations themselves. The multifunctional performance of technological innovations cannot be portrayed individually or independently of each other. Thus empirical simulation based studies of multiple interacting segments, with or without overlaps, are inherently interesting. Diffusions of multiple product generations and cross-segment interactions between generational segments as well as simultaneous consideration of both spatial and relational ties are also necessary to portray complex systems and their implications.

CHAPTER 3
NEW PRODUCT LAUNCH STRATEGIES: A SYSTEM DYNAMIC MODELING

Introduction

Background

Product launch, also called product commercialization, is considered the last stage of the NPD process (Cooper 1993; Crawford 1983). Consistent with previous research, this study views product launch as incorporating all the activities and decisions necessary to present a new product to its target market and thus to begin generating income from sales (Choffray and Lilien 1984; Yoon and Lilien 1985).

The product launch stage represents the largest investment in the entire process because of the combination of product and marketing expenditures incurred once a decision to launch is approved (Urban and Hauser 1993). For example, the Gillette Sensor launch cost $200 million in research, engineering and tooling, and $110 million in first-year television and print advertising (Hammonds 1990). Cooper and Kleinschmidt (1988) found that the average amount spent by industrial new product developers on commercialization was almost $434,000. More recent research has shown that product launch activities consume a significant amount of total new product costs, often exceeding the combined expenditures of all previous development (Beard and Easingwood 1996; Calantone and Montoya-Weiss 1993).

Product launch is also often the most crucial stage in the new product development (NPD) process. Campbell (1999) noted that even a superior and unique new product could fail due to a poor product launch. Empirical studies have also consistently shown that a proficient product launch greatly improves the chances of new product success (Calantone and Di Benedetto 1988a; Cooper 1979; Cooper and Kleinschmidt 1988; Maidique and Zirger 1984; Song and Parry 1996).

The Purpose of the Study

Even though the importance of product launch has been well acknowledged in the literature, product launch strategies have not been well studied, understood and managed (Calantone 1999; Guiltinan 1999; Hultink et al. 1998; Hultink et al. 1997). In particular, I find that the previously cited works have several shortcomings: 1) lack of an integrated framework that incorporates not only marketing, but also supply chain management perspectives of product launch strategies; 2) failure to consider apriori uncertainties that are intrinsic to product launch processes and 3) failure to consider the dynamic nature of the product launch process. I present the details of these shortcomings in the next section.

In this study, I propose an integrated product launch strategy framework that incorporates both the marketing and the supply chain management perspectives. The integrated framework argues that various and seemingly diverse product launch tactics such as pricing, advertising, channel development, production and inventory management can be investigated using a holistic view, in which product launch scale (which represents a firm's commitment to the launch) is a strategic level policy that influences how those launch tactics are devised and implemented. Both to demonstrate and to test the proposed framework, I develop and validate a system-dynamic model. This model not only considers the new product diffusion process and its responses to marketing and supply chain management policies, but also examines how those marketing and supply chain management policies evolve over time. In this model, marketing and supply chain policies are considered as dynamic processes, both because of the diffusion nature of the new product market, but also due to the interactions between marketing and supply chain and to interference from the focal firm's launch activities. The firm's launch polices, both at the strategic level and the tactical level, are also considered to be dynamic, since the two levels of launch policies interact with each other and respond to the feedback from the market and supply chain system. The model is developed and calibrated based on established product diffusion and new product management theories and empirical results.

The Structure of the Paper

The next sections of this paper feature the following: 1) a review of the existing literature and identification of research gaps; 2) specification of research objectives based on those research gaps: 3) presentation of a proposed integrated dynamic framework of product launch strategies that can be used to manage product diffusion processes and marketing uncertainties; 4) a review of the methodological basis for addressing the research objectives, and finally, 5) a summary list of the research questions, which are based on the research objectives and which can be addressed by this study's proposed methodology.

Gaps in Previous Research

The purpose of this section is to review several streams of literature related to new product launch strategies: a) market uncertainty related to new product launches; b) product diffusion literature; c) the supply chain management perspective of product launches, and c) literature on product launch strategies. The potential gaps and limitations of past research that are identified in the research literature form the foundation for the current study.

Market Uncertainty

Past literature shows that market uncertainties at the new product launch stage are the primary reason for many product launch failures. They cannot be eliminated, but they can be managed. Market uncertainties exist for a number of reasons. First, for new product development, forecasting can be prohibitively costly in time and resource commitment, and forecasts are as well subject to market volatility and competitive action (Page and Rosenbaum 1992; Song & Montoya-Weiss 1998). Second, uncertainties, defined as "not knowing which forces and trends really matter" (Marsh 1998, p.45), are largely unknowable, even after all possible analyses and forecasts. Third, new product launches are often dominated by market uncertainties.

At a macro-level, the environment surrounding current new product launches is far from stable, since globalization and technology are sweeping away market and industry structures (Bryan 2002). Unforeseeable events such as the 9/11 terrorist attacks, as well as geopolitical events such as events in the Mid-East, can also have profound impact on both macroeconomics and the markets for the new products. From a micro-level, new products – those that are either new to the market or to the firm (or both) (Booz et al. 1982) - are intrinsically associated with market uncertainties (as perceived by the focal firms), because historical data (from the market) and/or past experience (from the firm) cannot be used to make reliable forecasts. In fact, uncertainties are regarded as one of the primary exogenous sources that affect New Product Development (e.g. Lynn and Akgün 1998; Song and Montoya-Weiss 2001; Souder et al. 1998).

Product Diffusion Literature

In the marketing literature, the main impetus underlying diffusion research is the Bass model (Bass 1969), which assumes that potential adopters of an innovation are influenced by two means of communication – mass media and word of mouth. Over the years, various extensions of the Bass model have been developed. It has a very strong track record of fitting historical sales patterns, and the model is simple to understand and apply (Roberts and Lattin 2000).

However, when making sales forecast prior to product launch, the Bass model and its many extensions have to rely on managerial experience or historical data on similar products to "guess" the parameters and potential market size of a given product (Mahajan et al. 1995). This guessing method becomes unreliable especially when a product is relatively new to the market or to a firm. Therefore, the sales forecast can often differ greatly from the actual sales data.

The Supply Chain Management Perspective

Operation activities such as inventory management, transportation, and manufacturing have long been overlooked by the product launch literature (e.g., Choffray and Lilien 1984; Cooper 1998; Guiltinan 1999; Hultink et al. 1998; Hultink and Robben 1999; Hultink et al. 1997; Lambkin 1988; Yoon and Lilien 1985), with the exception of the seminal work by Bowersox, Stank, and Daugherty (1999). Marketing often emphasizes effectiveness goals such as market share, revenue, customer satisfaction, etc., while operations focuses more on efficiency measures, such as lowering costs (Crittenden et al. 1993; Karmarkar 1996; Shapiro 1977). For example, marketing and operations have conflicting costs and benefits related to production lead time, performance quality, conformance quality, volume variation, marketing mix variations and product customization (Karmarkar 1996).

The supply chain management perspective is a systematic view of the entire supply chain, instead of any individual element. As such, it requires integration, coordination, and collaboration across organizations and throughout the supply chain. This includes sourcing, manufacturing, and delivery processes from the point of raw material origin to the point of ultimate consumption (Stank 2002). As such, an integrated product launch strategy can be more adaptive to market uncertainties than is a supply chain management strategy.

Product Launch Strategy Literature

Launch strategy is often considered at two levels: 1) *the strategic level*, which includes such strategic decisions as target market, leadership, relative innovativeness, product strategy, market strategy, competitive stance, firm strategy, etc., and 2) *the tactical level*, which includes tactical decisions such as product, distribution, promotion, pricing, and timing (Guiltinan 1999; Hultink et al. 1998; Hultink et al. 1997).

Product launch strategies have not been well examined, understood and managed (Calantone 1999; Guiltinan 1999; Hultink et al. 1998; Hultink et al. 1997). Early studies related to product launch strategies focus on elements of launch strategies such as market entry (Farrell and Saloner 1986; Green et al. 1995; Green and Ryans 1990; Harrigan 1981; Lambkin 1988), advertising expenditures (Yoon and Lilien 1985), price (Choffray and Lilien 1984; Lambkin 1988), breadth of product assortment (Biggadike 1979), product development cycle time (Robertson 1993), and so on. These studies are either too narrowly focused or too "elementary" (Greenley 1994), or lack the systematic and integrated framework needed to help managers analyze launch situations and devise launch strategies accordingly (Guiltinan 1999).

Recent works by Guiltinan (1999) and Hultink et al. (1997; 1998) are more comprehensive; however, they also are problematic. For example, in the Hultink et al (1997) view, the best product launch strategies are niche marketing strategies, a view that apparently contradicts market realities, which indicate that many mass marketing launches are also very successful. Meanwhile, Guiltinan has taken a contingency perspective and has suggested that the choices of launch strategies depends upon the focal product's relative innovativeness and compatibilities; however, these aspects of marketing are often unknown by product managers before product launch when market uncertainties are high.

In addition, the past literature on product launch strategies often takes a static approach, which assumes that the launch strategy is static and pre-defined before the product launch. This is quite an effective approach when market uncertainties are low and the environment is rather stable. This approach follows traditional strategic thinking (for a review of conventional strategic frameworks, see Ghemawat 1999), which requires ex-ante market assessment and budget development before product launches. The static approach also fits nicely with top management's requirements for budget control and accountability. However, this approach is rather problematic for "really" new products, where market uncertainty is high. Calantone (1999, p. 507) has lamented that forecast-based launch plans "became highly risk-laden bombs waiting to oversize (usually) the manufacturing base, distribution promises to channel allies, and proposed advertising budgets."

Summary of previous research gaps

The literature review in the previous section reveals the following research gaps in past studies:

1. Market uncertainties are often overlooked or not fully accounted for by many studies on product launch strategy. Therefore, product launch studies need to provide a means to deal with market uncertainties.

2. Supply side restrictions and the coordination between supply chain activities and marketing activities are not considered in product launch studies (with only a few exceptions). Therefore, product launch strategy studies need to consider supply side launch activities such as manufacturing, logistics, etc.

3. Most research explicitly or implicitly assumes that product launches are pre-defined before launch and are static. That is, the product launch is a calculated speculation based on forecasts and market analyses prior to product launch. Product launch strategies do not change much during the product launch process. Therefore, product launch studies need to adopt a more dynamic approach, allowing the product launch to evolve as the situation changes.

4. It is unclear in the past literature how tactical versus strategic level launch decisions are aligned and how individual tactics such as pricing, advertising, channel management, manufacturing and inventory control, etc. coordinate with each other. Therefore, a theoretical framework is needed to integrate tactical and strategic level launch decisions and to align various tactical launch decisions with the overall launch strategy.

5. Few studies address resource commitment issues for product launches.

Research Objectives

The objective of this research is to develop an integrated theoretical framework regarding successful ways to manage product launches under high market uncertainty.

1. The theoretical framework must incorporate both the marketing and the supply chain management perspectives.
2. The framework must address launch management issues on both a strategic level and a tactical level, so that various and seemingly diverse product launch tactics such as pricing, advertising, channel development, production and inventory management can be investigated from a holistic viewpoint.
3. The framework must model the dynamic processes of product launches.
4. The framework must consider not only the new product diffusion process and its responses to marketing and supply chain management policies, but also examine ways in which those marketing and supply chain policies evolve over time.
5. The framework must model the dynamic processes of new product diffusions, the dynamic interactions between the market and the supply chain, and management's actions and the feedback from the market and the supply chain system.

The purpose of the following proposed theoretical framework and the methodological basis and the model proposed in the subsequent section is to ac

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address the research gaps identified in this the previous section of this work and to answer the proposed research objectives that have been identified in this section.

Theoretical Framework to Address the Research Objectives

Product Launch Scale and Market Uncertainty

In this study, at the strategic level, the focus is on one key dimension of product launch – product launch scale (see Figure 3-1), which is defined as the resource commitment that a firm makes during product launch. It has long been noted that resource commitment plays an important role in determining the speed of technology diffusion (Robinson and Gatignon 1986). According to Kuester et al. (2000), marketing-mix decisions (such as pricing and advertising), plant size and other nonreversible assets are all key indicators of the firm's resource commitment to product launch. Firms often adopt penetration strategies that entail aggressive pricing and high resource commitments to advertising, the sales force, and promotional activities.

The selection of such penetration strategies is driven by several objectives: 1) to gain rapid market acceptance, 2) to stimulate demand through a diffusion effect, 3) to benefit from cost reductions through learning effects, and 4) to discourage competitors from taking an equally strong stance in the market. However, sometimes a skimming strategy is more appropriate, as when the diffusion rate is slow and does not respond to the focal firm's actions very well.

As Figure 3-1 shows, product launch scale dictates a firm's pricing, advertising and promotion, product, sales force management, channel, logistics, an

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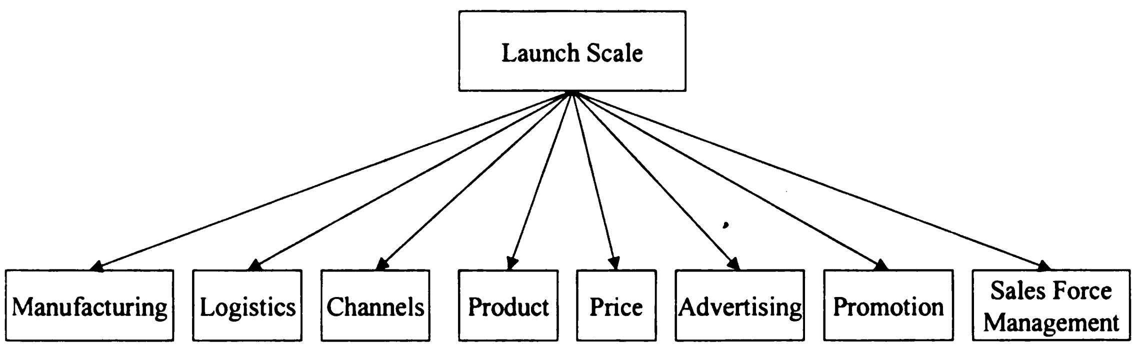
and manufacturing tactics. For example, a large launch scale often implies a mass marketing strategy that reveals such features as low price, high channel intensity, high inventory, a high production rate and production capacity, heavy advertising and promotion, etc. On the other hand, a small launch scale might be based on a niche marketing strategy featuring high price, low channel intensity, low inventory, low production rate and production capacity, light advertising and promotion, etc.

Figure 3-1 Product Launch Scale



However, due to the market uncertainties intrinsically associated with product launch, any speculation (based on some type of market research and forecast) could be wrong. That is, the scale of a product launch could be either too large or small compared to the actual market demand, which is the result of complicated interactions of the diffusion process and firm's actions. As Table 3-1 suggests, based on some forecasts, a firm can take either: (1) a "fat" launch (i.e. large launch scale), which dictates a large size target market, large inventory deployment, and large manufacturing capacity; or (2) a "narrow launch" (i.e. small launch scale), which calls for niche marketing featuring small inventory deployment and manufacturing capacity.

If the forecast is right, then the chosen launch strategy matches the market and the product launch is successful. However, if the forecast is wrong, the fat launch leads to oversupply with excessive inventory and manufacturing capacity, which results in financial losses. The lean launch can lead to short supply, which can result in lost market share and other opportunity costs. For example, when the satellite telephone company, Iridium committed $5 billion to launch a satellite network in an attempt to capture the mass market for wireless communications, it took a gamble. Iridium's failed as the market changed and few people wanted its costly and heavy Iridium phones. Meanwhile, others who succeeded with high stakes gambles (e.g. Steve Jobs with the launch of Macintosh Computer) are heralded as heroes.

Table 3-1 Forecast-Based Speculations

	Actual Demand: Low	Actual Demand: High
Predicted Demand Low* = Narrow Launch	Success	Opportunity Costs
Predicted Demand High* = Fat Launch	Oversupply with Losses	Success

- *Forecast-based speculation.*

In order to manage market uncertainties, this study takes the position that the product launch strategies should allow flexibilities for new product managers to adjust the launch scale and to adapt to emerging market opportunities and risks. According to Mintzberg and his colleagues (Mintzberg 1978; Quinn et al. 1988), strategies may be thought of as both intended and emergent. Intended strategies represent the plans developed by traditional strategy formulation in i

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which markets are assessed and budgeted programs are developed (Andrews 1987; Anthony 1988; Anthony 1965).

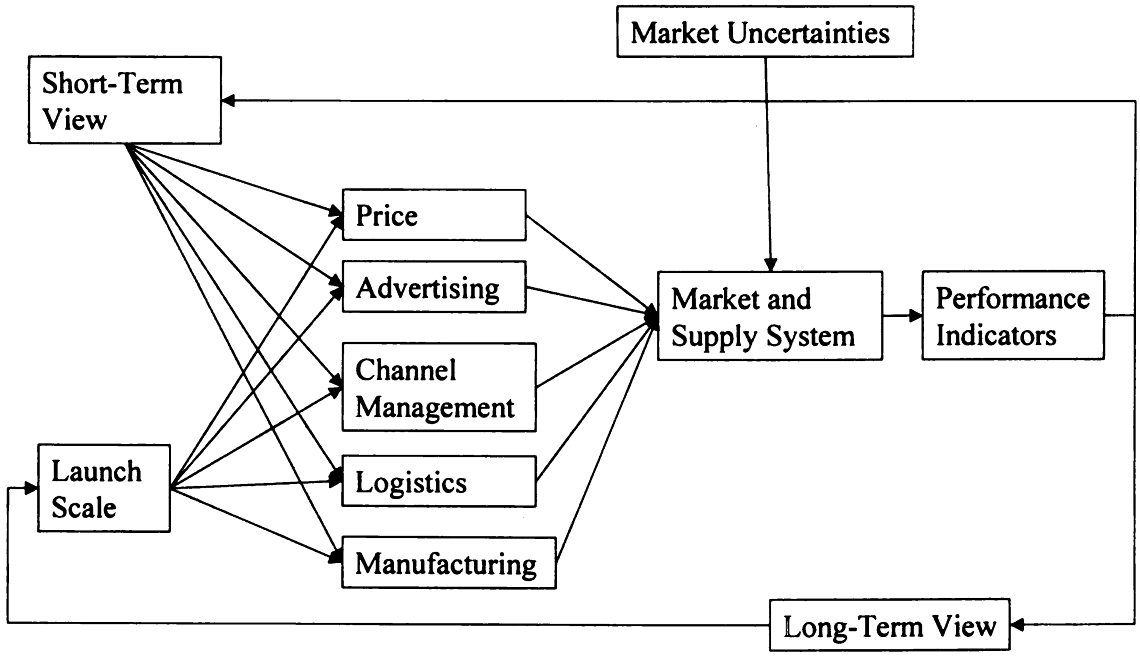
Emergent strategies, on the other hand, represent ideas that have surfaced from an organization's interactions with its customers and markets. These interactions may suggest tactics that would not have been considered during formal planning (Mintzberg 1978). When uncertainties are high, intended strategies fail because they are based on the assumption of synthesis from analysis, rather than on the intuition of marketing strategists (Andrews 1999). The strategic flexibility perspective proposes a middle ground. It suggests that instead of planning for a particular future market scenario, firms should plan necessary flexibilities that allow for emergent strategies, thus allowing for spontaneous response to changing environments (Sanchez 1997).

The Proposed Theoretical Framework

Based on the previous arguments, this researcher proposes a framework (see Figure 3-2) that integrates both launch scale and its tactical components and shows how these components respond to feedback from the marketplace as well as to changes made accordingly. In the proposed theoretical framework, launch tactics such as pricing, advertising, channel management, production and inventory management affect the marketplace and the supply chain through their respective mechanisms. Consequently, these tactics result in performance changes from the supply chain and from the marketplace.

These observable indicators of performance changes are then sent back to the focal firm's management. Based on those indicators, the firm forms both a short-term view and a long-term view of the product launch. The short-term view provides a basis for taking immediate action based on established launch policies at the tactical level. Meanwhile, even though the long-term view may produce slow reactions to the immediate performance changes, a long-term view helps to adjust the launch scale, which, in turn, fine tunes the existing tactical level launch policies. Market uncertainty, as an exogenous variable, is not determined by the system. Rather, it affects the quality of the firm's forecasts and the subsequent launch scale speculation.

Figure 3-2 Theoretical Framework



Methodologies

System Dynamics Methodology

As shown in Figure 3-2, the proposed framework is a rather complicated model even at its most aggregate level. Several processes, such as the diffusion process, the market response process, and the pricing, advertising, production inventory management process are intertwined with one another. It is rather challenging to model such a dynamic, complex system with interactions of the agents over time. Such a system is constantly changing, tightly coupled, governed by feedback, nonlinear, history-dependent, self-organizing, adaptive, characterized by trade-offs, counterintuitive, and policy resistant (Sterman 2001). Therefore, the proposed framework cannot be dealt with effectively using conventional methodologies that often take some piecemeal, static, and linear modeling approaches.

A solution lies in systems thinking: i.e., to see the world as a complex system in which "you can't do just one thing" and in which "everything is connected to everything else." Using a holistic worldview, a manager would be able to learn faster and more effectively, would be able to identify the high leverage points in systems, and would thus possibly avoid policy resistance. A systemic perspective would enable a manager to make decisions consistent with the long-term best interests of the system as a whole.

System dynamics modeling (SDM) fits all the above requirements. It uses simulations to build virtual or micro-worlds in which researchers and managers can develop decision skills, conduct experiments, and play. However, it is not designed to predict the future, but rather to help in understanding the current phenomenon.

SDM is based on the work of Forrester (1968), which has been formalized more recently by Coyle (1996), Maani and Cavana (2000), and Sterman (2000). SDM has been used in several studies evaluating NPD programs and processes and in organizational decision-making (Black and Repenning 2001; Milling 1996; Repenning 2002; Repenning and Sterman 2002). In this study, Vensim, an SDM programming package by Ventana Systems (1992), is used to build the model of approximate differential equations that represents the dynamic changes occurring in a new product launch process over time, where new product diffusion is facilitated by the focal firm's marketing, manufacturing and logistics activities across the entire supply chain.

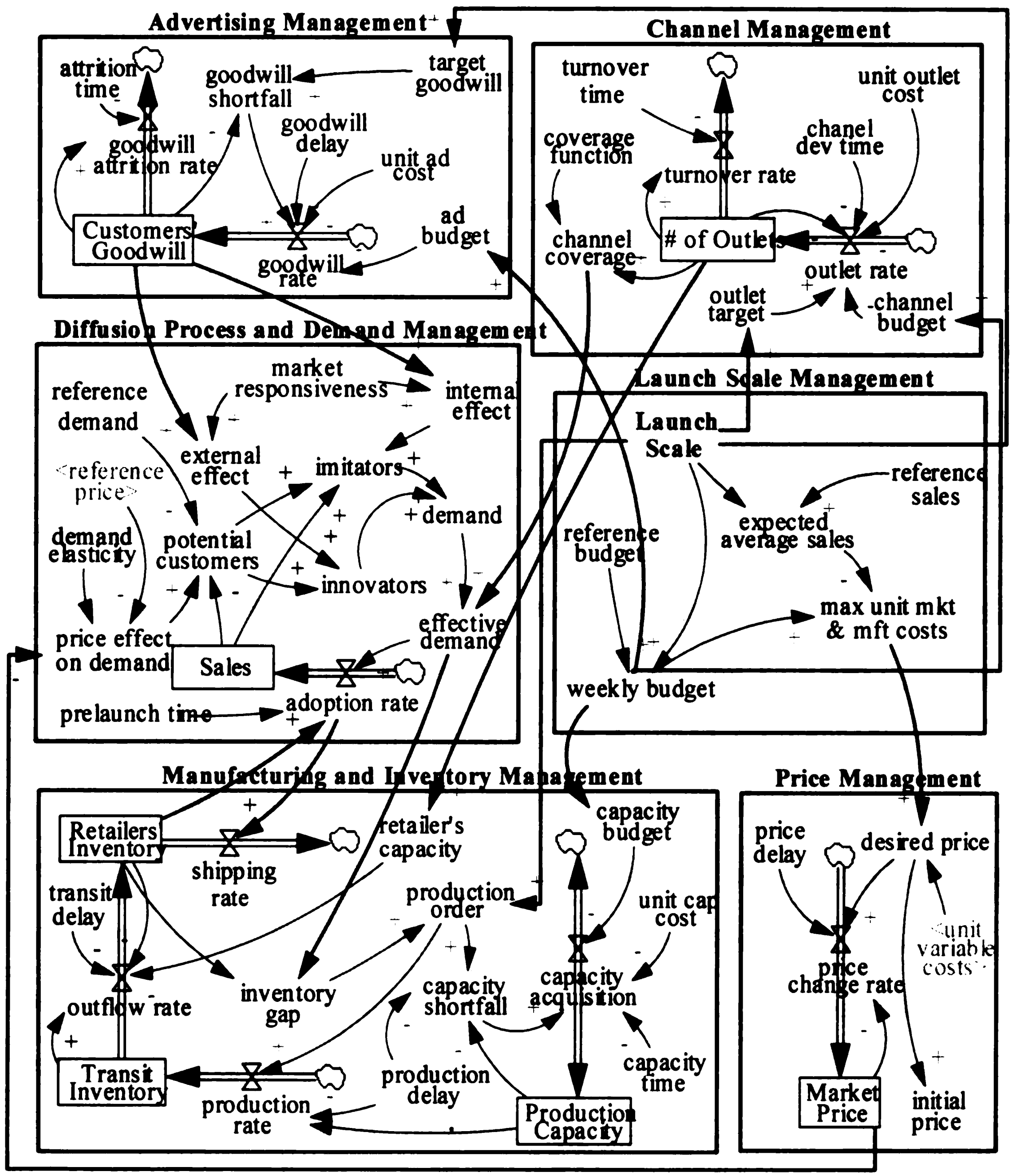
Criteria for Evaluating System Dynamics Models

In evaluating system dynamics models, a number of criteria provide guidelines for specifying the model and the standards against which it can be judged (Barlas 1996; Forrester and Senge 1980; Sterman 1984). At the initial model building stage, system dynamics researchers emphasize capturing the policies (decision rules) used in the situation (Forrester 1994), which can be conscious or unconscious, rational or irrational. Policies in the model are reflected by equations and table functions, both of which may represent nonlinear relationships. Decisions for actions are concrete applications of those policies or decision rules. In SDM, the first step is descriptive, that is, to capture policies based on qualitative and quantitative sources of data. Once model is built, verified, and validated by the models' users, then SDM modelers shift to normative domains – such as policy design.

Because decisions are policies are represented explicitly, formulations should reflect the existing understanding of behavioral decision-making involved in the processes being modeled. For the current study, the model is developed based on two sources: 1) existing literature on new product diffusion, advertising and channel management, manufacturing and inventory management and 2) interactions with new product managers.

Figure 3-3 shows the details of the stock and flow diagram of the base model, which is consisted of 7 modules: product diffusion and demand management, advertising management, channel management, pricing management, manufacturing and inventory management, launch scale management, and the accounting module (not shown in Figure 3-3). The following sub-sections offer a detailed description of the model, where all variables in the model are denoted with italic font style.

Figure 3-3 The Basic Model



New Product Diffusion and Demand Management Module

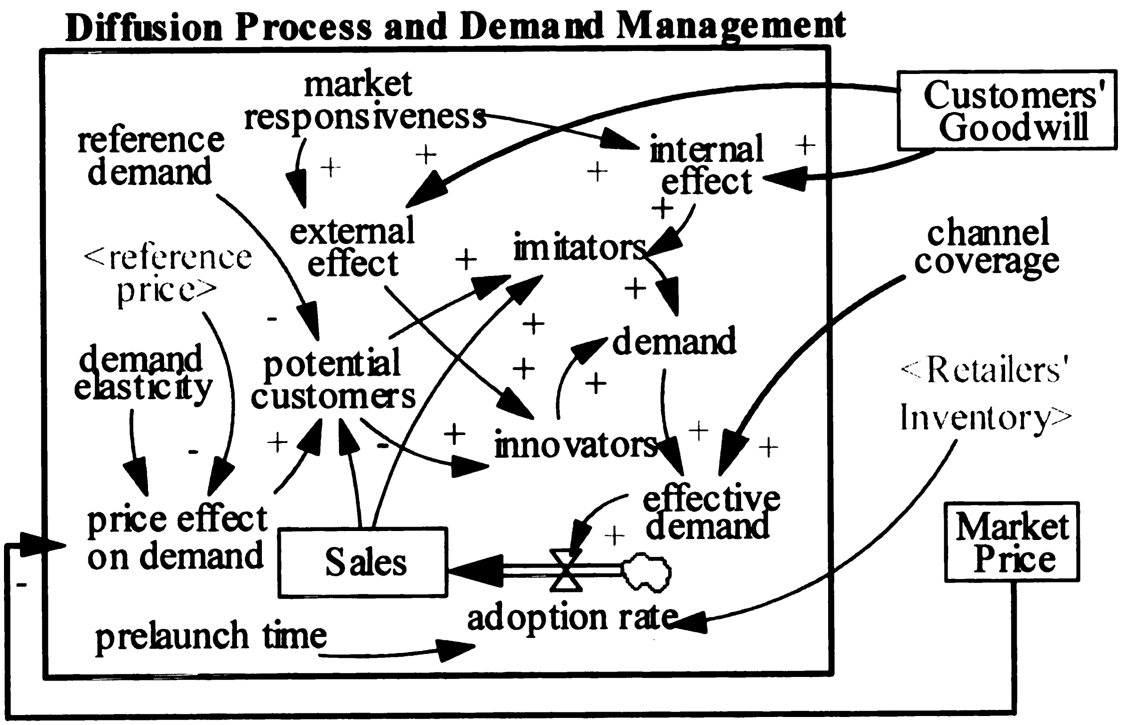
The product diffusion module (see Figure 3-4) models the product diffusion process, and the impact of the focal firm's actions in the process. The module is developed based on the basic Bass model (1969), which posits that for durable consumer products, *potential customers* and the *external effects* (such as mass media) determine the demand from *innovators*, while the size of the adopters (i.e. the *sales*), the size of the *potential customers*, and the *internal effects* (i.e., interpersonal communications) drive the demand from imitators.

Both the *external effects* and *internal effects* are influenced by *customers' goodwill* related to the new product. However, due to market uncertainties, *the effectiveness of customer's goodwill* is usually not known to the new product managers before and during a new product launch, and thus *effectiveness of customer's goodwill* is an exogenous variable in this model.

The *demand* is the sum of demand from innovators and imitators, while *effective demand* is the part of the total demand that can be covered by the distribution channel. The portion of *effective demand* that can be met by the *retailers' inventory* determines the number of adopters (i.e. adoption rate), which accumulates and becomes total *sales*.

Following a standard treatment on modeling price and demand relationship, the model posits that *market price of the product* and *demand elasticity* determine the price's effect on demand, which multiplied by *the reference demand*, then minus total *sales* yields the size of *potential customers*.

Figure 3-4 Diffusion Process and Demand Management



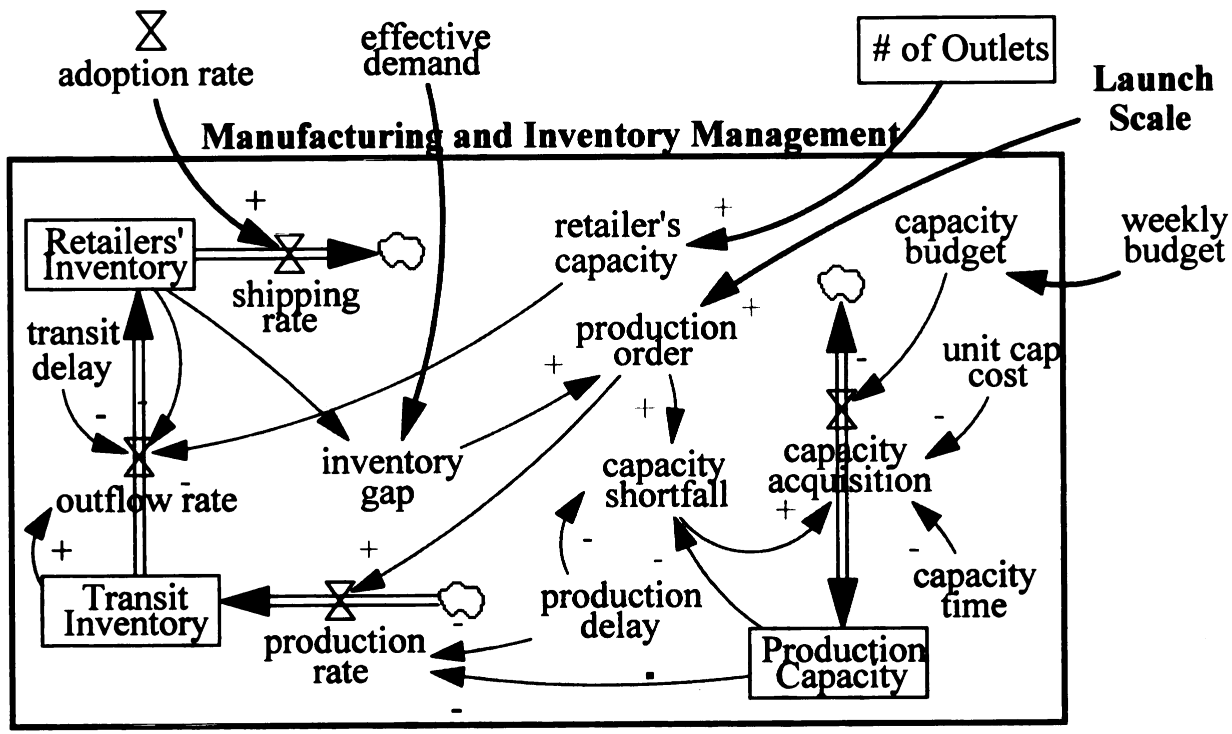
Manufacturing and Inventory Management Module

The manufacturing and inventory management module (see Figure 3-5) deals with the dynamic relationships among inventory, production rate, and production capacity.

Within the module, there are primarily **two loops**. The **first loop** deals with production and inventory. When the *retailers' inventory* level is less than the *minimum inventory* level (which is four times the current effective demand), an *inventory gap* is generated. Based on the *launch scale* and the *inventory gap*, the size of the *production order* is then decided. The *production rate* is the *production order* divided by *production delay*, which is also restrained by the *production capacity*. *Transit inventory* is the term designating finished products before they reach the retailers and which is a function of *production rate*, minus *transit rate*. The *transit rate* is the *transit inventory* divided by *transit delay*, which is also restrained by the *maximum retailers' inventory capacity* decided by the *number of retailer outlets* that carry the new product. The *retailers' inventory* is sold at a *shipping rate* that is decided by the new product *adoption rate*.

The **second loop** deals with the dynamics of *production capacity*. The difference between *production order* and *production capacity* is the *capacity gap*, which determines the *capacity acquisition rate* with *capacity acquisition time*. The *capacity acquisition rate* is also limited to the budget constraint due to the *capacity budget* and *unit capacity cost*.

Figure 3-5 Manufacturing and Inventory Management



Advertising Module

The advertising module (see Figure 3-6) deals with how advertising decisions affect the customers' goodwill toward the new product. There is only one loop in this module. The product *launch scale* determines the *target goodwill*, which, combined with the current *customers' goodwill*, determines the customers' *goodwill gap*. The *goodwill gap* divided by the *goodwill delay* is the *goodwill rate*, which is also limited by the current *ad budget* and the *unit goodwill costs*. The *ad budget* is a function of the *total weekly budget*. The *customers' goodwill* is decided by the *goodwill rate* and the *attrition rate* over time, and the initial *goodwill rate*. The *goodwill attrition rate* models the fact that *customers' goodwill* toward a product deteriorates overtime if no effort is made to maintain the goodwill.

Channel Module

The channel module (see Figure 3-7) has only one loop. This module deals with how channel management decisions affect the channel coverage of the demand for the new product. In the module, the number of the *target retailer outlets* is determined by the new product *launch scale*. The difference between the *target outlets* and the actual *# of outlets* divided by the *outlet development delay* affects the *outlet acquisition rate*, which is also limited by the *unit outlet costs*, and the *channel budget*. The *channel budget* is, in turn, a function of the *weekly budget*. The current *# of outlets* is a function of the *outlet rate* and the *outlet turnover rate*. A table function is used to convert the current *# of outlets* to the *channel coverage*. The table is an "S" curve based on empirical evidence shown in Kotler and Lilien (1982).

Figure 3-6 Advertising Management

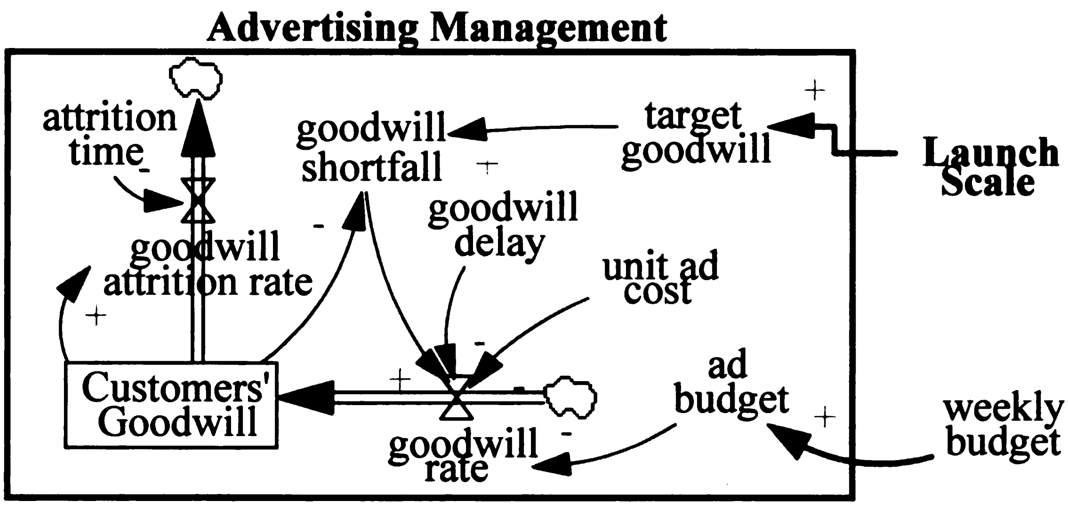
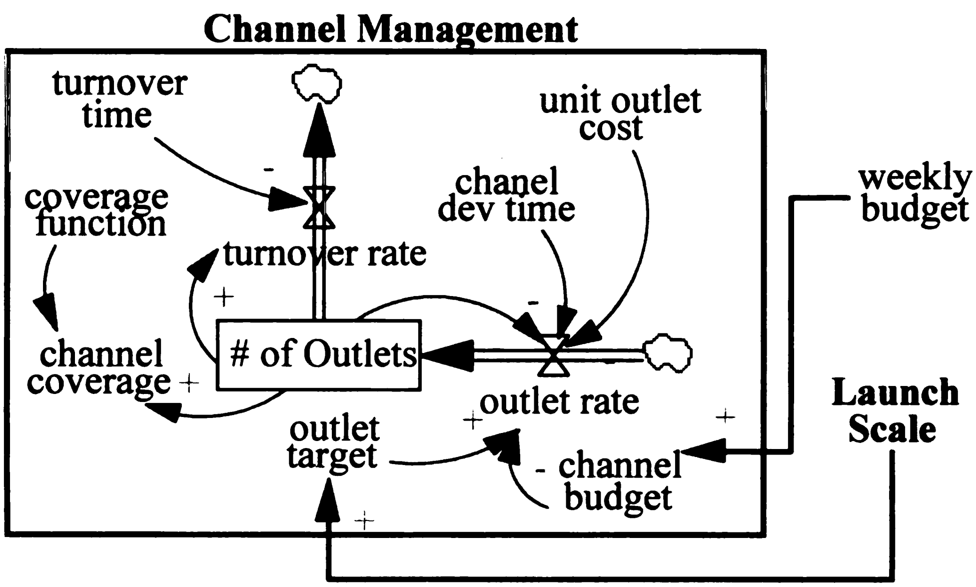


Figure 3-7 Channel Management

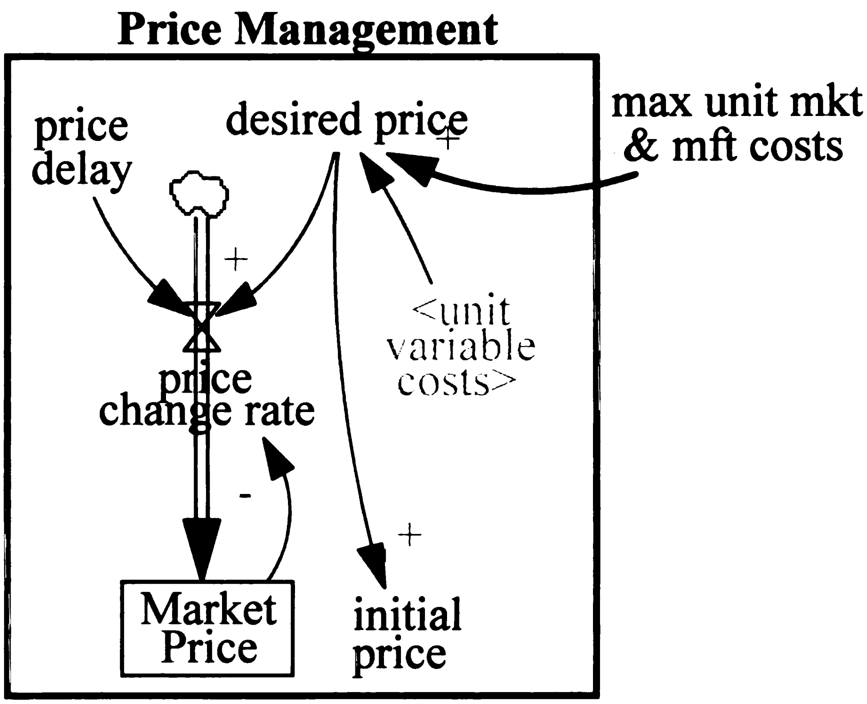


Price

Management Module

The price management module (see Figure 3-8) deals with how the market price is set for the new product. In the module, the *desired price* is the sum of the *variable unit costs*, and the estimated *maximum manufacturing and marketing costs* (that is advertising, channel management, and production capacity costs). The difference between the *desired price* and the *market price* divided by the *price delay* is the *price change rate*, which affects the *market price* with the *initial market price*.

Figure 3-8 Price Management



Launch Scale Management Module

The product launch scale management module (see Figure 3-9) deals with the central concept of the study, that is, how the new product launch scale affects how many new resource commitments are made to the product launch in each period of the launch process. In the basic model, *launch scale* is static, and thus is an exogenous variable. It directly affects the *target goodwill*, *outlet target*, and the size of *production order. Launch scale* also determines the *weekly budget* based on the *reference budget*, and thus *launch scale* indirectly affects the *ad budget*, the *channel budget*, the *production capacity budget*, and the *desired price.* In addition, the *weekly budget* and the *expected average sales* per week--which is a speculation by the management regarding average sales based on *reference sales* and *launch scale*--determine the *maximum manufacturing and marketing costs per product unit,* which, in turn, influence the *desired price* for the new product.

Accounting Management Module

The accounting management module deals with how costs for all marketing and manufacturing activities, product revenue, and profit are calculated for the model.

In the model, total costs is a function of weekly costs accumulated over time, while weekly costs is the sum of weekly fixed costs and weekly variable costs. The weekly fixed costs consist of inventory costs, channel spending, ad spending, and capacity spending.

Inventory spending is calculated with the current inventory (the sum of transit inventory and retailers' inventory), the current average unit costs, and the weekly interest rate. The channel spending is calculated by the multiplication of outlet rate and unit outlet cost. The ad spending is the multiplication of the goodwill rate times the unit ad cost. The capacity costs is the multiplication of the capacity rate and the unit capacity cost. Meanwhile, the weekly variable costs is the multiplication of the weekly production rate and the unit variable costs, which is a function of the initial variable costs minus the multiplication of the current total production and the marginal cost reduction. The use of the marginal cost reduction is to model the fact that variable costs usually decrease when more products are produced and more experience is gained.

The current revenue rate is a function of the market price and the adoption rate (i.e. current sales rate). Unit costs can be calculated by the total costs divided by the total production. Meanwhile, the current profit rate is a function of the revenue rate, the market price, and the unit costs. The total revenue and profit over time can be obtained from the revenue rate and the profit rate respectively.

Figure 3-9 Launch Scale Management

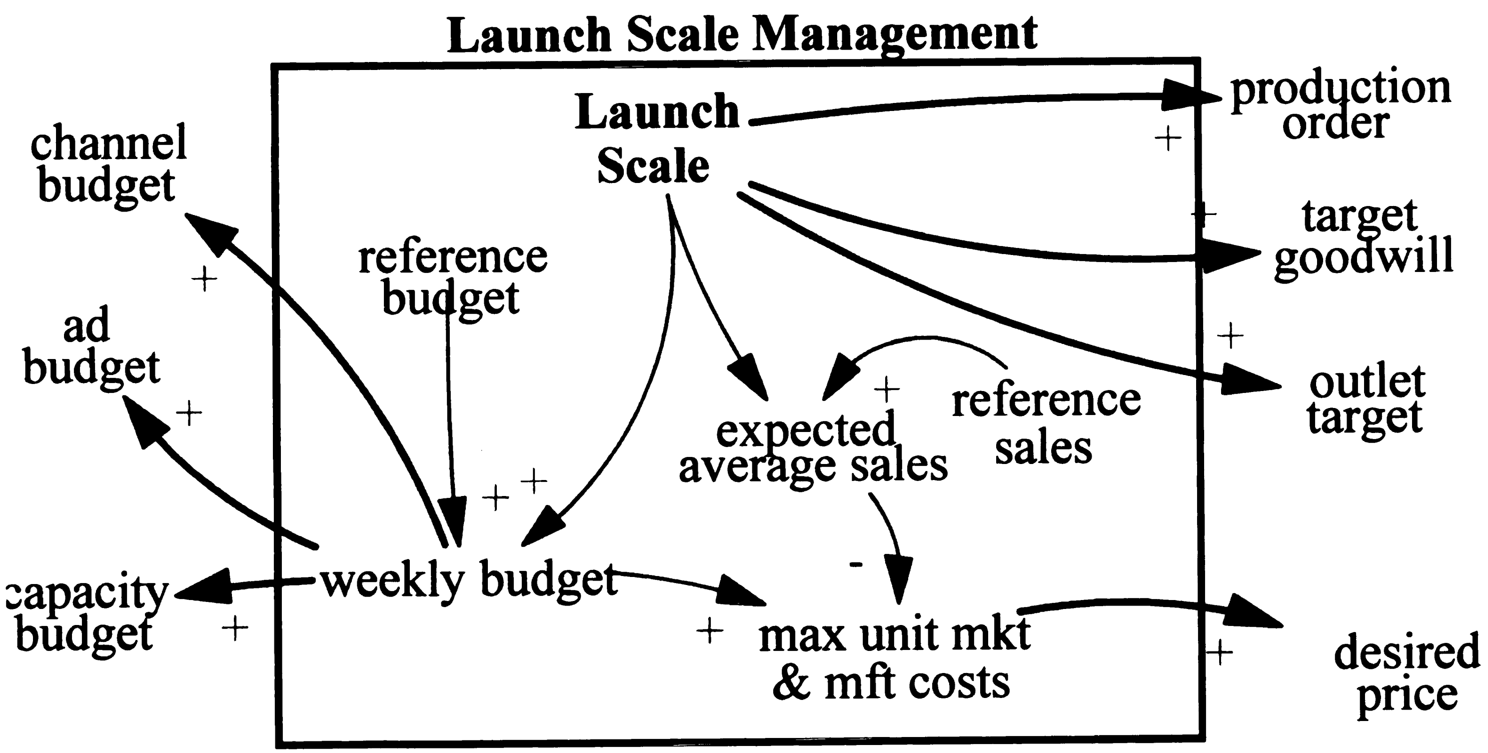
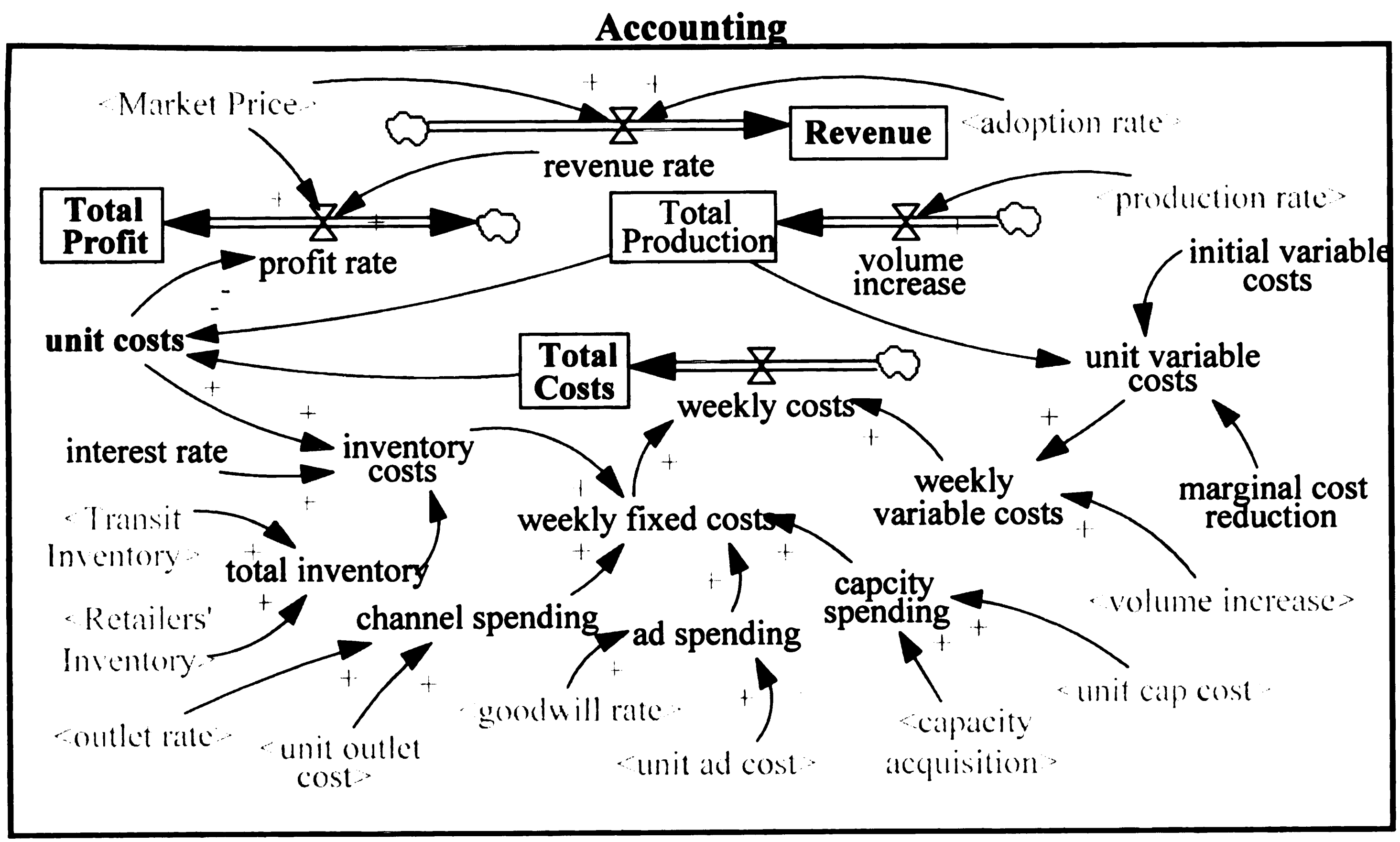


Figure 3-10 Accounting

Figure 3-10 Accounting



The Basic Model

The Assumptions

In the basic model, it is assumed that managers can manage a new product launch using two sets of policies on resource commitments. One is the short-term policies, such as adjusting production level, production capacity, inventory level, customers' goodwill, channel coverage, and price level based on some long-term targets. The other is the long-term policy, which can be changed by adjusting the new product launch scale, which affects various long-term product launch targets. However, in the basic model, the long-term policies are static, that is, the product launch scale is fixed during the new product launch. The launch scale is adjustable to different degrees in those models with non-static launch strategies.

In all of the models used in this study, managers are assumed to be able to observe the various stated variables and to make decisions accordingly. However, it is also assumed that the managers do not have accurate information on most of the parameters of the model. For example, managers can only guess the size of the market and the value of the internal effect. In fact, all of the later analyses on launch strategies are based on those scenarios when wrong forecasts are made using those parameters, particularly the internal effect.

The Simulation of the Basic Model

The time unit of the simulation is a week, and the total simulation period is 600 weeks (about 12 years, assuming 50 working weeks/year). The first 12 we

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weeks of a simulation are the pre-launch periods, during which initial product capacity is acquired, initial inventories are produced, and channels and customer's goodwill are developed based on policy targets and budgets that are determined by the launch scale. The sales of the new product starts in the 12th week of the simulation (see Figure 3-4).

Analysis and Results

The Research Design

New Product Launch Strategies: Static vs. Dynamic

In the previous sections, I propose both a theoretical model and an operational model regarding how to integrate various new product launch tactics into a coordinated strategy from the perspective of resource commitment. In the following sections, using the proposed model, I investigate the performance of different launch strategies under market uncertainties. Specifically, two categories of new product launch strategies are studied: a *static launch strategy* and a *dynamic strategy*.

In a *static launch strategy*, the launch scale is determined before the product launch based on pre-launch forecast/speculation. The launch scale does not change during a product launch. Therefore, two types of static strategies based on the size of the launch scale are studied: 1) the narrow launch strategy, in which very small resources are committed to a new product launch (i.e., a low launch scale); and 2) the fat launch strategy, in which large scale resources are committed to a new product launch (i.e., a high launch scale). In a dynamic

launch strategy, the initial launch scale is set before the product launch. However, the launch scale is dynamically adjusted according to the actual launch performance.

Market Responsiveness and Market Uncertainties

The market uncertainties imply that the pre-launch forecast for the market's response to a new product launch can be either favorable or unfavorable. Therefore, for a new product launch strategy to manage market uncertainties, it must be able to handle both favorable and unfavorable market responses to the new product launch. In this study, a variable called **market responsiveness** is used (see Figure 3-4) to model the degree that the market responds to the product launch efforts (i.e., advertising and promotion). Specifically, high market responsiveness implies high internal effects and external effects of the new product diffusion process, which lead to earlier demand takeoff for the new product.

The market responsiveness reflects the nature of the products and the nature of the market (such as market heterogeneity) which are independent of customers' goodwill and thus also not dependent on advertising. For a product that is either new to the market or to the firm, or both (i.e. high market uncertainties), market responsiveness is not known to the new product managers before the new product launch.

The Research Design

In this study, both static and dynamic launch strategies are tested under two scenarios: high market responsiveness and low market responsiveness (see Table 3-2). The static strategy is examined based on the basic model. The dynamic strategy is investigated based on the dynamic model, which uses different policies for the launch scale.

Table 3-2 Research Design

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Scenarios</td></tr>
<tr><td>High Market Responsiveness</td><td>Low Market Responsiveness</td></tr>
<tr><td rowspan="2">Static Launch Strategies</td><td>Fat Launch</td><td></td><td></td></tr>
<tr><td>Narrow Launch</td><td></td><td></td></tr>
<tr><td>Dynamic Launch Strategies</td><td>Dynamic Launch</td><td></td><td></td></tr>
</table>

The Evaluation Criteria for New Product Launch Strategies

There can be many aspects to evaluating new product launch strategies, such as profit, market share, cost efficiency, etc. In this study, the total profit for the new product launch is used as the main criterion for evaluating the performance of the launch strategies. There are several reasons for this approach. First, for most firms, the ultimate goal for a new product launch is to maximize its long term profit. Second, other performance measures such as market share, cost efficiency, etc., are also aimed at increasing the new product project's long-term profit. Third, in this study, the new product launch strategies are studied from a medium-term perspective, in which profit is also the most appropriate performance measurement.

Different from other studies on new product diffusions and new product launches, this study takes a medium-term perspective (i.e., 5 to 6 years from a product launch time). Use of the medium-term perspective is due to the dynamic behavior of the new product diffusion process and because the delayed impacts of new product launch policies can only be studied in a longitudinal study, both reasons which preclude use of any short-term approach. In addition, a long-term approach that covers a product's entire product life cycle is also not appropriate, since the new product loses its newness after it reaches the mature stage of its life cycle, which can be managed with conventional product management strategies instead of product launch strategies. Furthermore, because of market uncertainties, especially competitive pressures, it is rather critical for firms to maximize their new products' medium-term profits instead of their long-term profits.

The Results of Static Launch Strategies

The two types of static launch strategies are studied under two different scenarios: *high market responsiveness* and *low market responsiveness*.

<u>Scenario #1: High Market Responsiveness</u>

Figure 3-11 shows the new product diffusion curves for both the narrow launch strategy and the fat launch strategy. The fat launch strategy clearly leads to a more rapid diffusion process, which reaches its peek at about week 250, with a peak adoption value near 3000 units/week. Meanwhile, the diffusion curve for the narrow launch strategy is rather flat. It reaches its peak at around week 700, with a peak value around 800 units/week. Figure 3-12 shows the total profits for the two strategies from week 12 (0 to12th week is the pre-launch period) to week 300, which reflects the medium-term profitability. At the start of the launch, both strategies lose money, even though the narrow launch strategy loses less money than the fat launch strategy and returns to profitability slightly faster. However, although the fat launch strategy's increase in profit is much steeper than that of the narrow launch strategy, it clearly exceeds that of the narrow launch strategy at week 80, and its profit is more than two times that of the narrow launch strategy's at the end of week 300, with a value above $600 million.

Figure 3-11 Adoption Rate

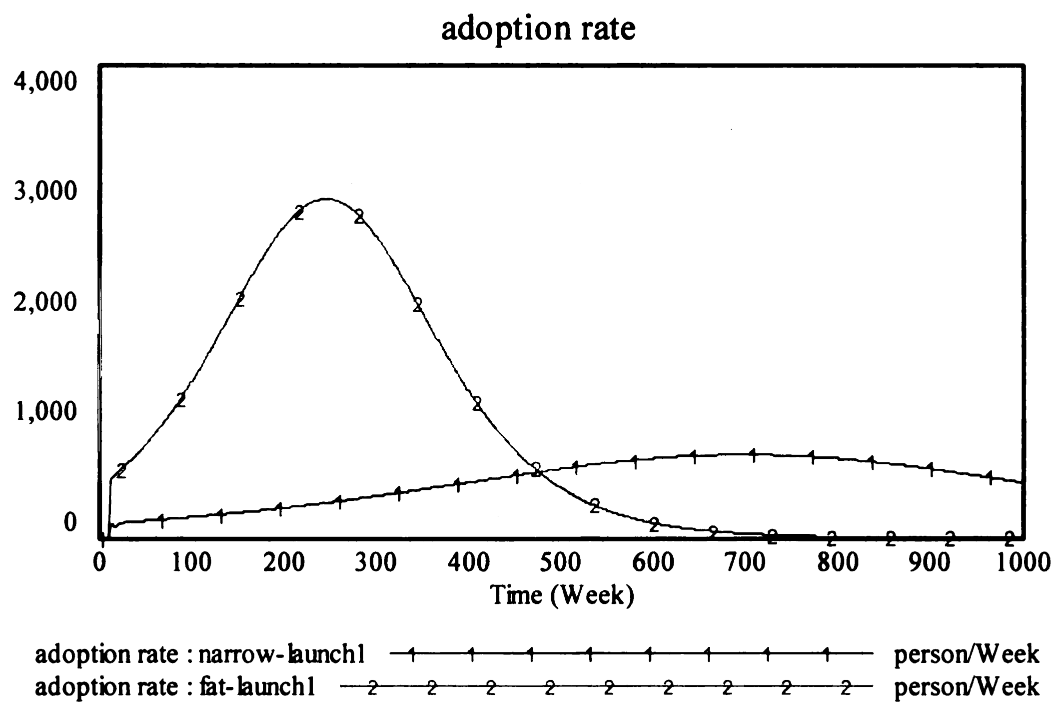
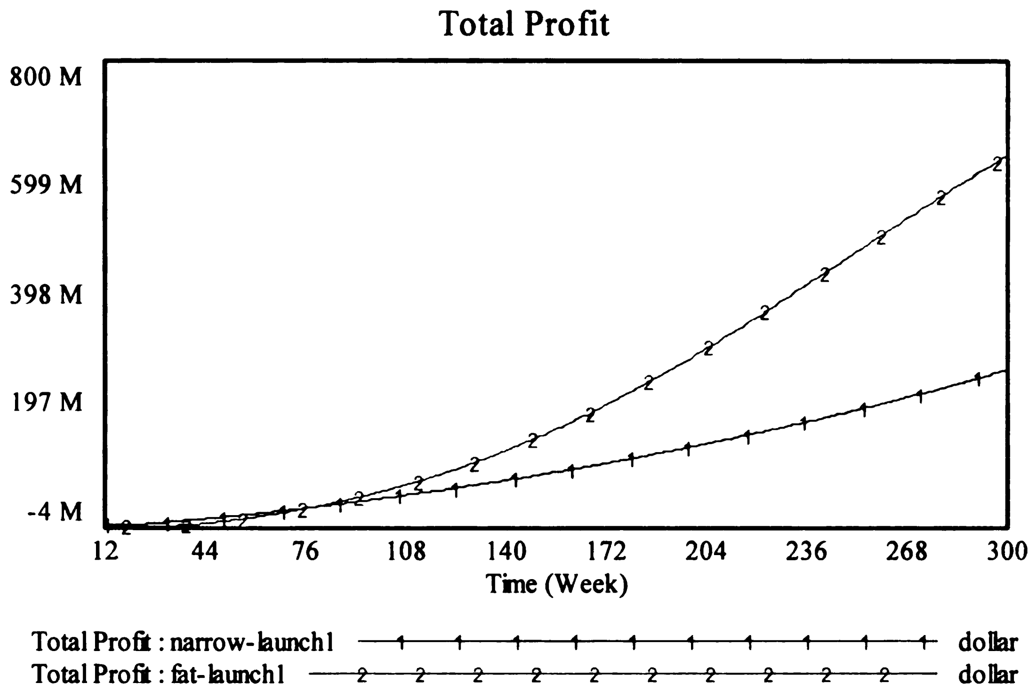


Figure 3-12 Total Profit



The unit costs (see Figure 3-13) for both launch strategies decrease over time, as more products are produced and sold to share the manufacturing and marketing costs. Even though the narrow launch strategy makes a smaller resource commitment to the product launch than does the fat launch strategy, the narrow launch strategy's unit costs are almost two times larger than that of the fat launch strategy. This difference is because there is greater demand and thus a much larger number of products to share the higher total costs of the fat launch's strategies.

Meanwhile, the unit price (see Figure 3-14) of the fat launch strategy is also more than three times lower than that of the narrow launch strategy because the unit gross price margin needed for the fat launch strategy is much lower than that of the narrow launch strategy. Because the launch scale is static for the two strategies investigated here, the price for both strategies is only slightly reduced over time, due to the reduced variable costs, which are driven by increased total production volume. In addition, most of the time the prices for both strategies are larger than the unit costs, a fact which implies that the new product launches are profitable for *both* strategies.

Figure 3-13 Unit Costs

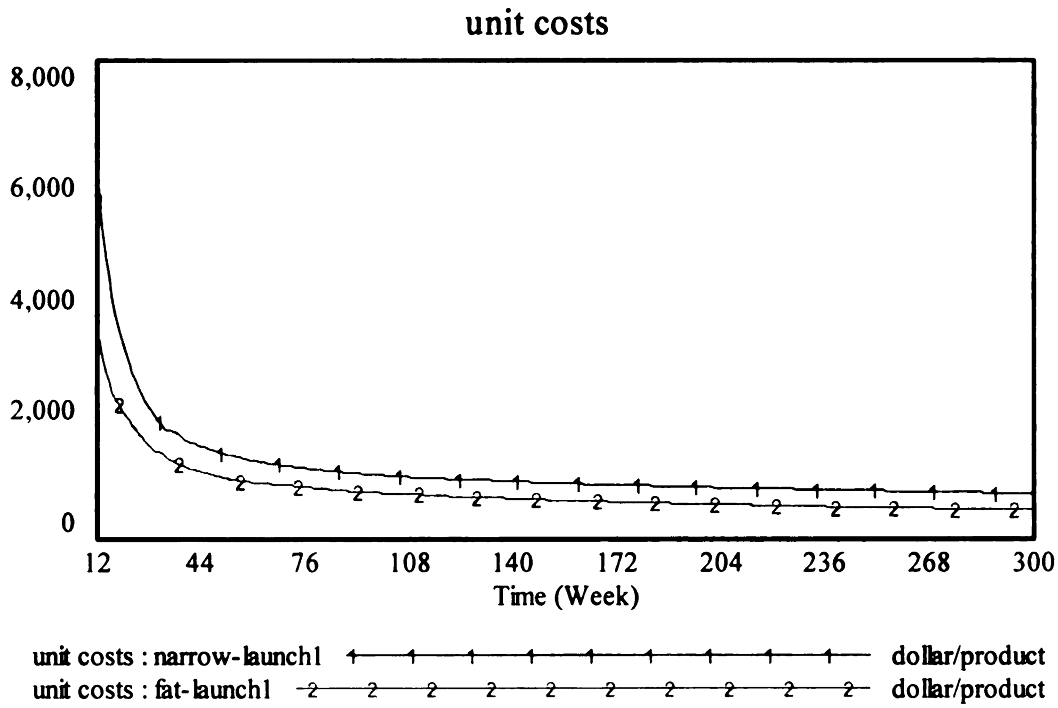


Figure 3-14 Market Price

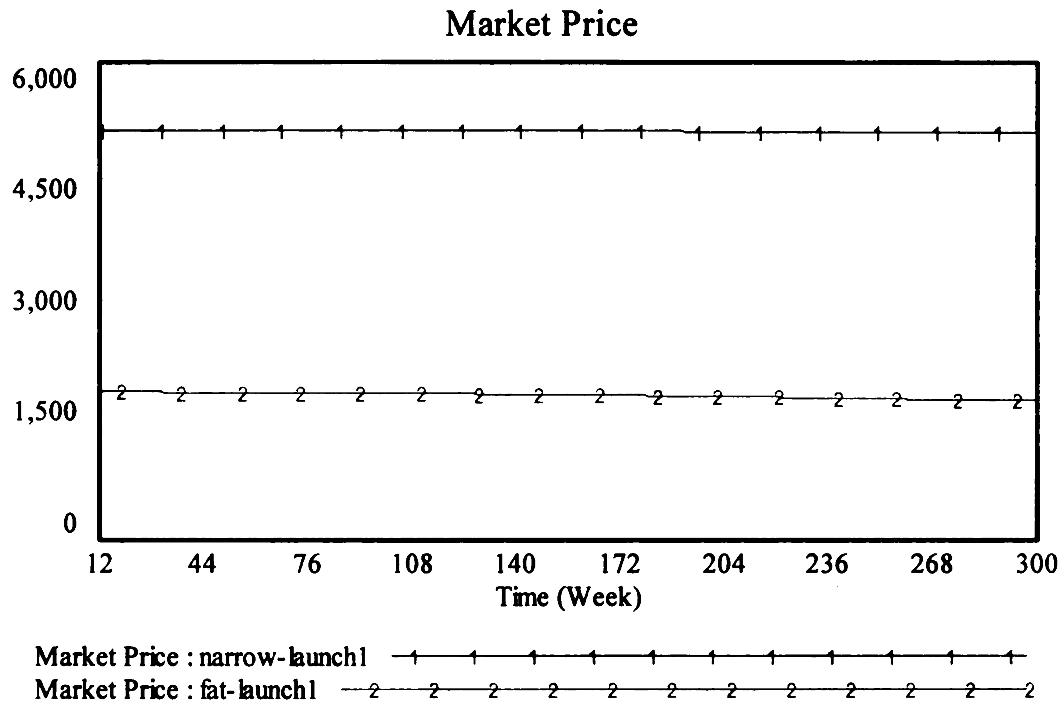


Figure 3-15 and 3-16 display the channel coverage and customers' goodwill during the product launch period. The values of these two variables are determined by the new product launch scales and the budget. Obviously, the fat launch strategy dictates a much larger channel coverage and greater customer goodwill than does the narrow launch strategy.

Figures 3-17, 3-18 and 3-19 illustrate the dynamic behaviors of retailers' inventories, production capacities and production rates for the two strategies. Again, the fat launch strategy results in larger inventory deployment, production volume and capacity, all of which are needed to facilitate the higher demand generated by the strategy's pricing, channel management, and advertising policies.

Figure 3-15 Channel Coverage

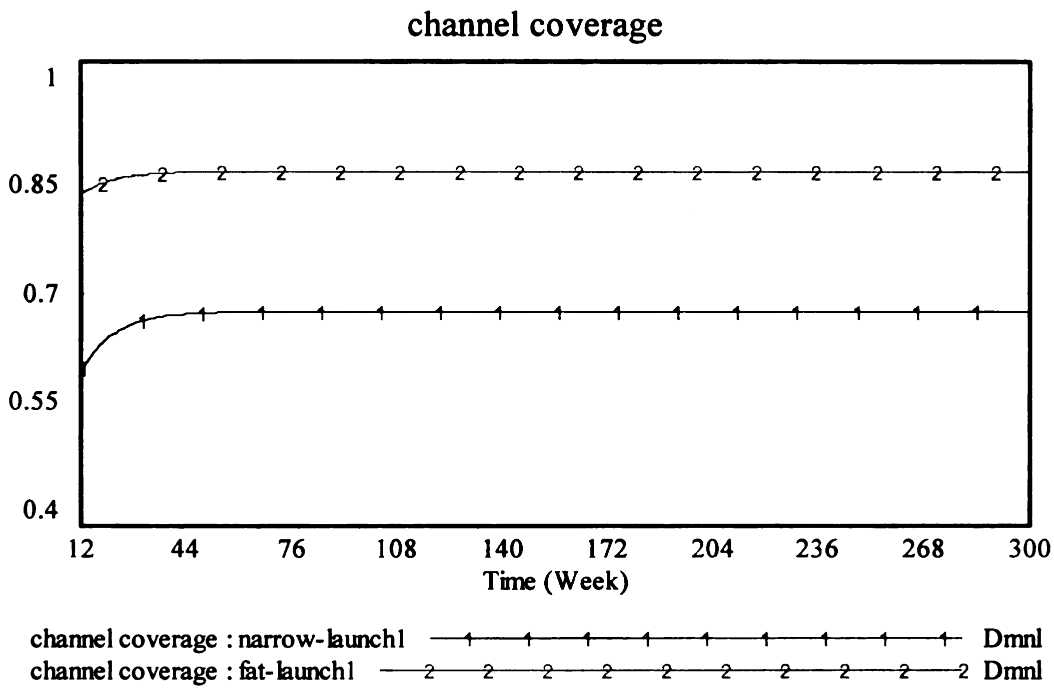


Figure 3-16 Customer's Goodwill

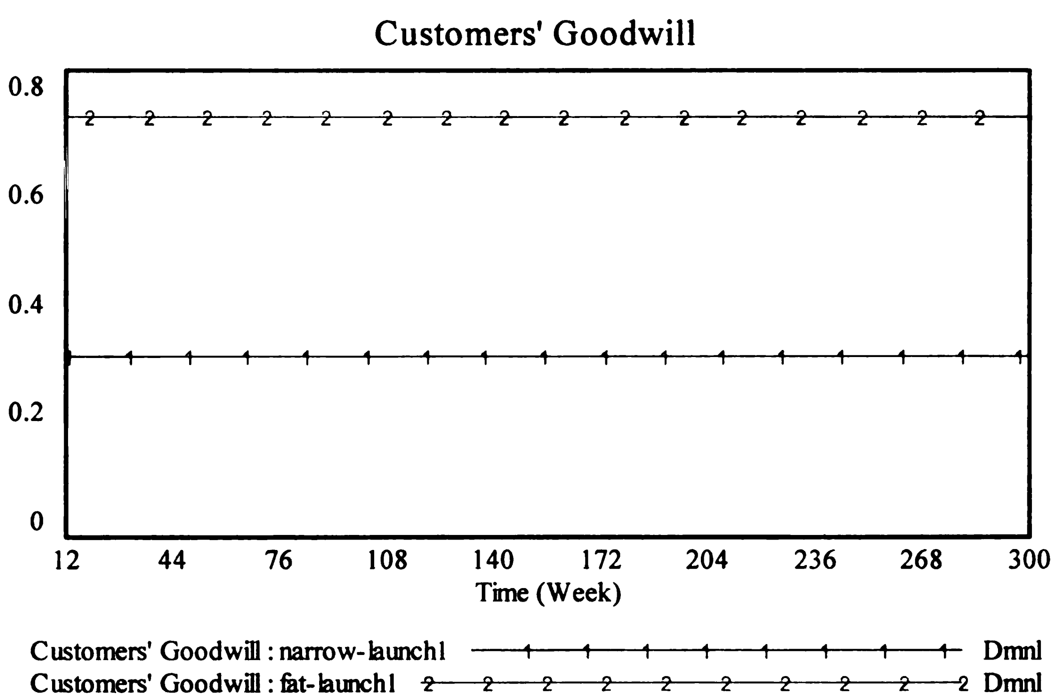


Figure 3-17 Retailer's Inventory

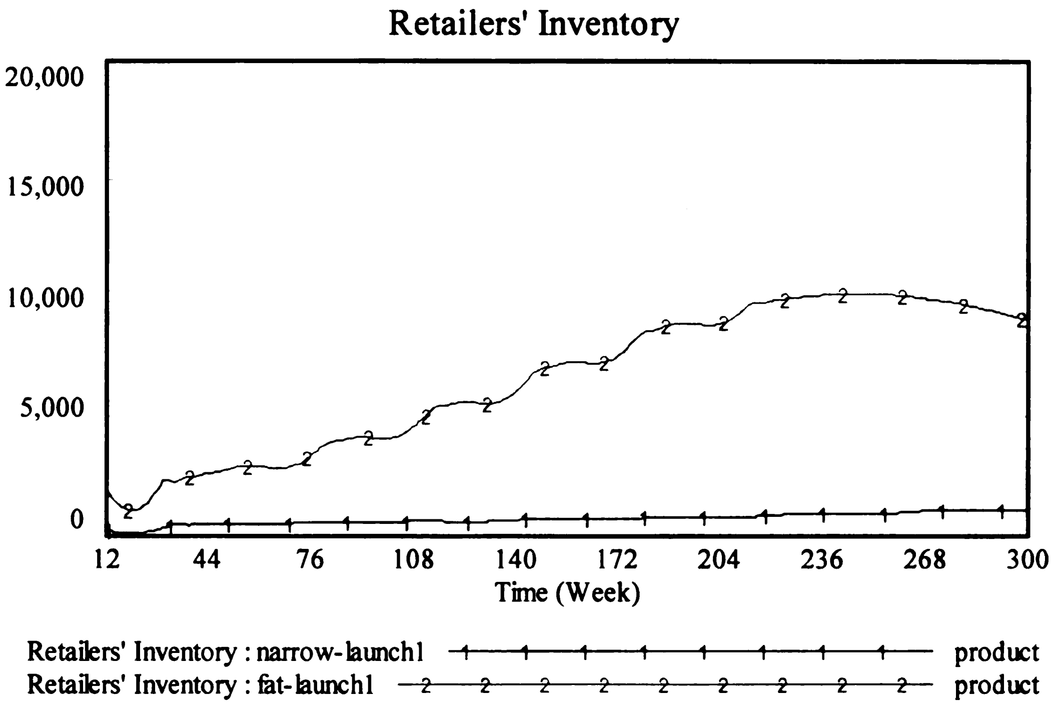


Figure 3-18 Production Capacity

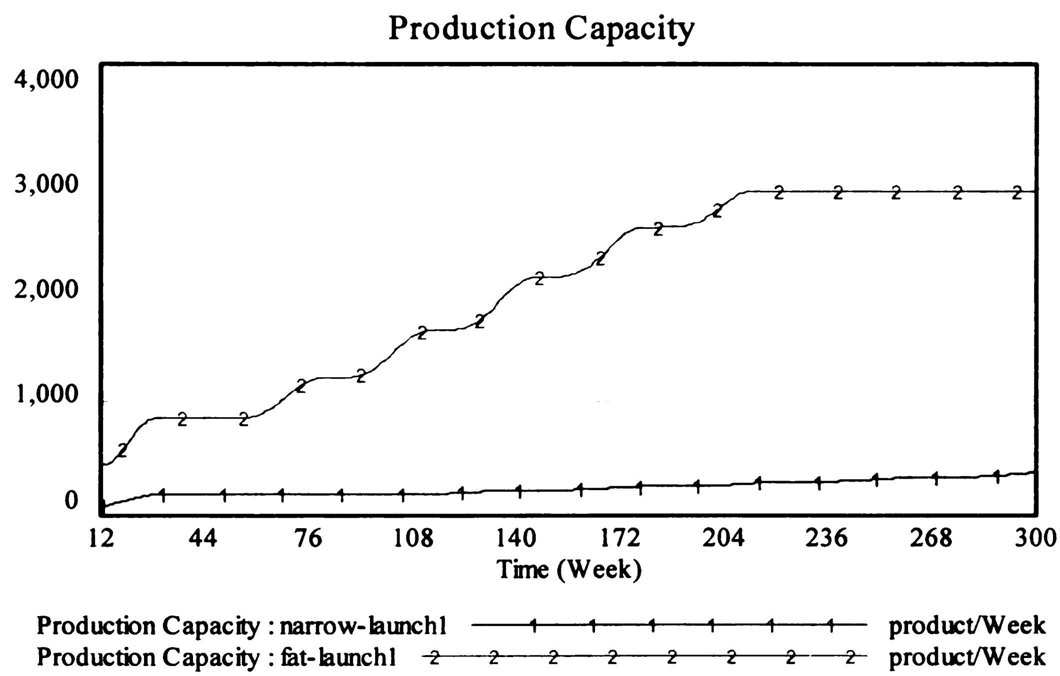
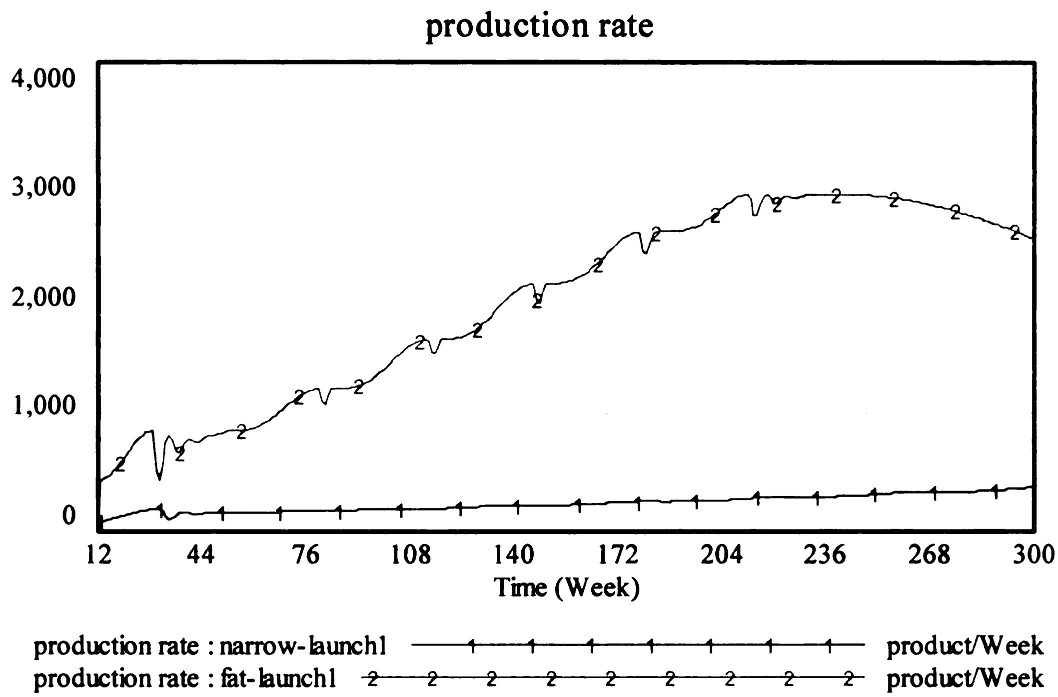


Figure 3-19 Production Rate



In sum, in the scenarios of high market responsiveness, the fat launch strategy greatly outperforms the narrow launch strategy in such areas as profit, sales, costs, etc. Such performance is due to the fat launch strategy's aggressive pricing, advertising, production and inventory investment, and channel coverage, all of which accelerate the diffusion process greatly.

Scenario #2: Low Market Responsiveness

Figure 3-20 shows the product diffusion process for the two static launch strategies under the condition of low market responsiveness. Again, the adoption rate for the fat launch strategy is much greater than that of the narrow launch strategy. However, the diffusion speeds for both strategies are rather slow, as neither of them reaches its peak value even at week 1000. The maximum adoption rates during the first 1000 weeks are about 480 units/week and 60 units/week for the fat launch strategy and the narrow launch strategy respectively, rates which are far below the expected average sales (see Figure 3-21) for the two strategies.

The total profits for the two static launch strategies are shown in Figure 3-22, which reveals that the narrow launch strategy outperforms the fat launch strategy considerably. Even at week 300, the fat launch strategy still has a net loss of about $8 million, while the narrow launch strategy has a $19 million profit at that time. The reason for the success of the narrow launch strategy is that its profit margin is much higher than that of the fat launch strategy, which is negative during most of the launch time. In fact, the narrow launch's unit costs (see Figure 3-23) is only $1000 higher than that of the fat launch strategy, but its market price (see Figure 3-24) is about $3400 higher than that of the fat launch strategy. Even though the adoption/sales rate (see Figure 3-20) of the fat launch strategy is higher than that of the narrow launch strategy, that rate is not high enough to compensate for the fat launch's disadvantage in its profit margin per unit.

Figure 3-20 Adoption Rate

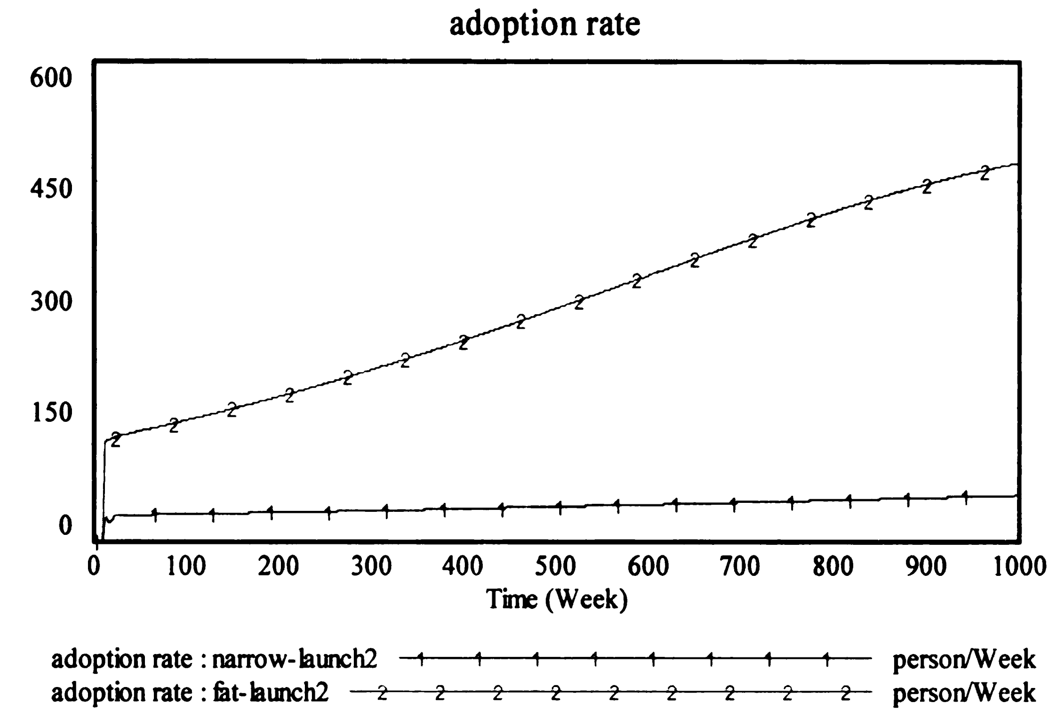


Figure 3-21 Expected Average Sales

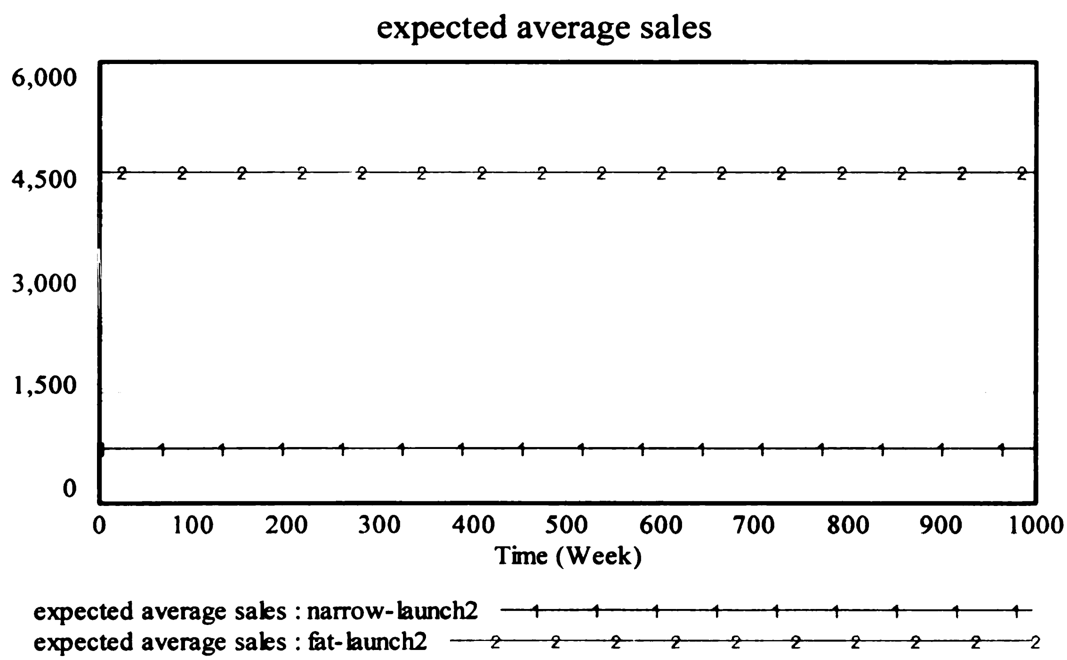


Figure 3-22 Total Profit

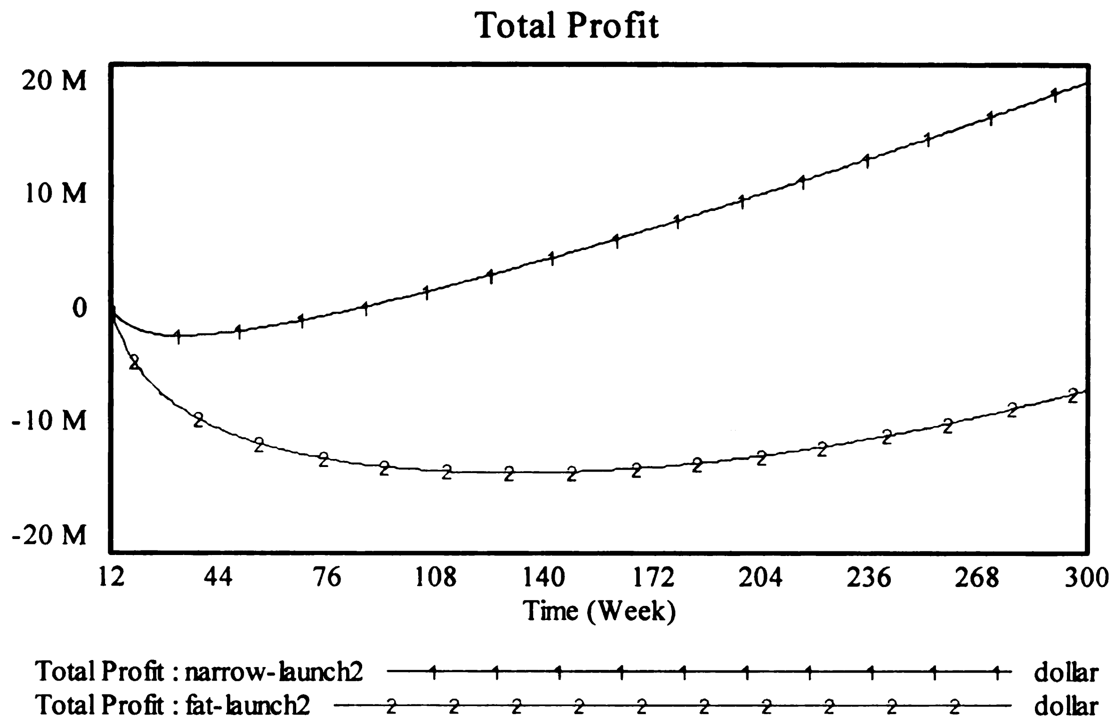


Figure 3-23 Unit Costs

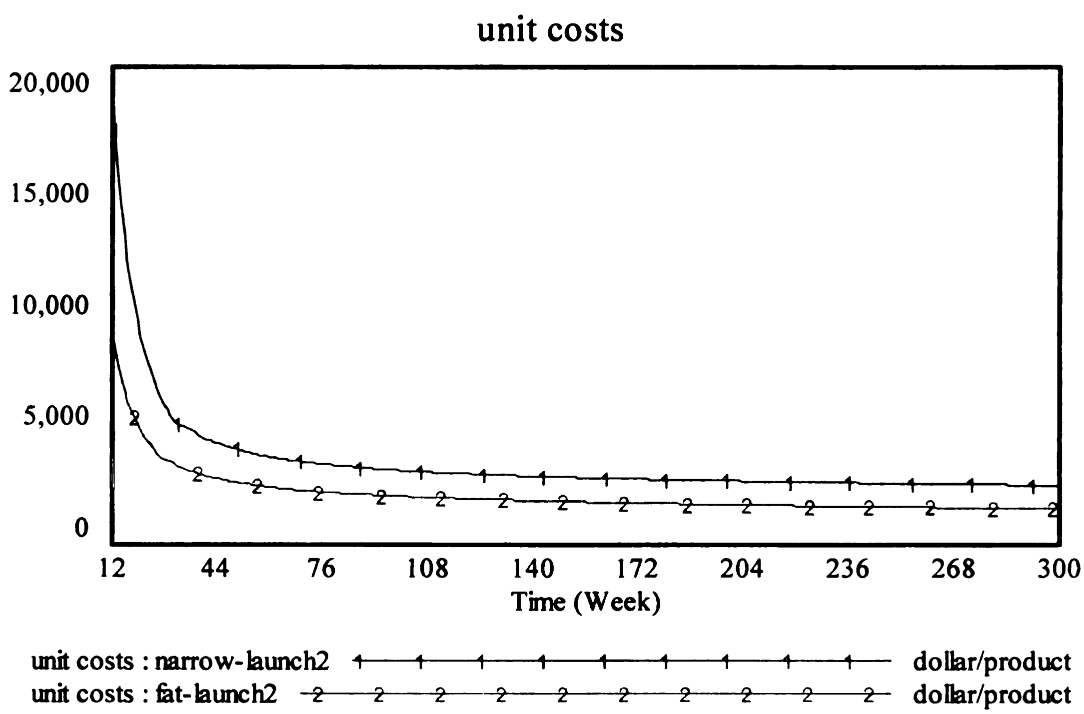
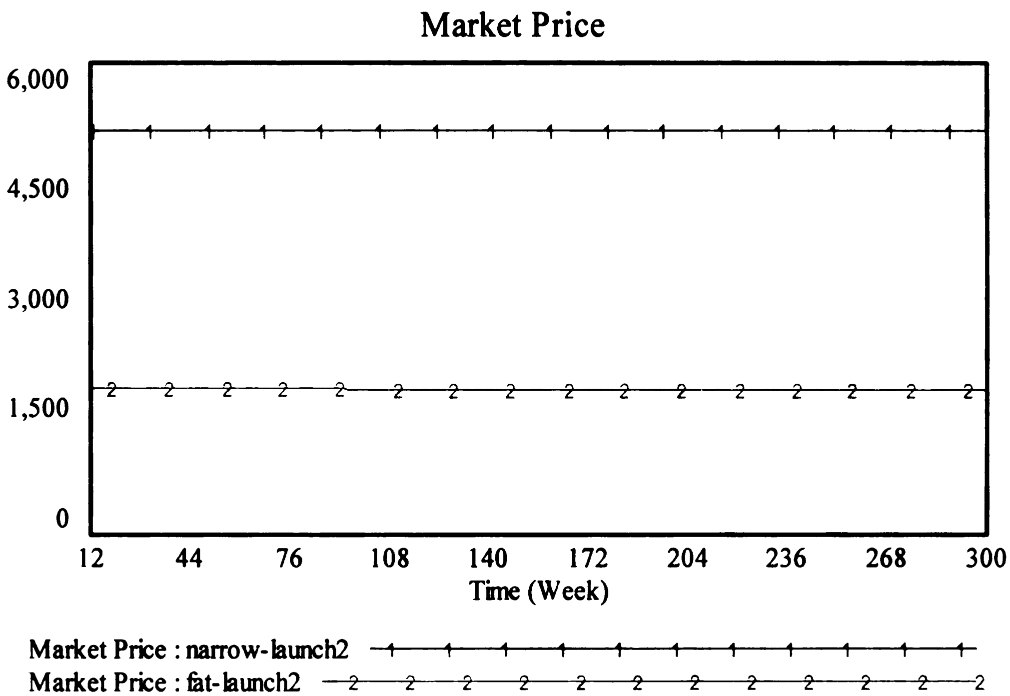


Figure 3-24 Market Price



Under the low market responsiveness scenario, the market's response to the fat launch strategy's heavy commitment to advertising is rather low. Consequently, the diffusion process cannot fully take advantage of the increased potential market size, channel coverage, inventory deployment, and production capacity generated by the fat launch strategy. The resources committed by the fat launch strategy are largely ineffective and wasted and cannot be recovered over time because the sales rate is flat. Contrary to the fat launch strategy, the narrow launch strategy commits only very few new resources to the product launch and charges a high price. Therefore, the narrow launch is able to make a decent profit, even under very unfavorable market conditions.

Findings for the Basic Model

Even though the results from the basic model are not surprising, the basic model serves several purposes. First, it replicates the new product launch process from an integrated framework that incorporates launch policies across the entire marketing and supply chain management functionalities. Second, it demonstrates that new product launch scale (that is, the level of resource commitments for a new product launch) is critical for new product launch performance. Third, it further validates the system dynamic models that are developed in this study. Fourth, it demonstrates why new product launches are so difficult to manage and so prone to failures. Specifically, a few findings can be obtained from the results of the basic model:

Finding #1: Static launch strategies can only be successful when the actual market conditions for a new product launch is the same as the pre-launch forecast. Therefore, static launch strategies are rather ineffective in managing market uncertainties associated with new product launches.

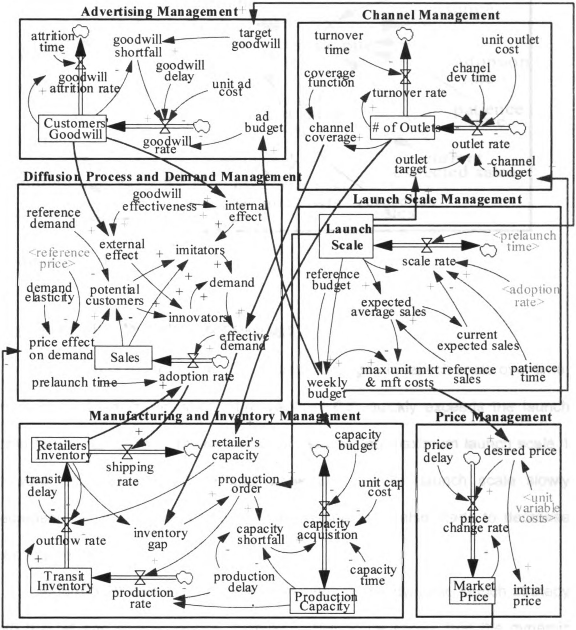
Finding #2: New product launch policies at the tacit level (that is, at the individual functionality level), are rather ineffective for optimizing the entire new product launch process. Therefore, it is critical to develop launch policies at the strategic level.

Finding #3: The new product launch scale is a highly relevant, and in fact, critical strategic dimension in managing new product launches.

The Results of the Dynamic Launch Strategy

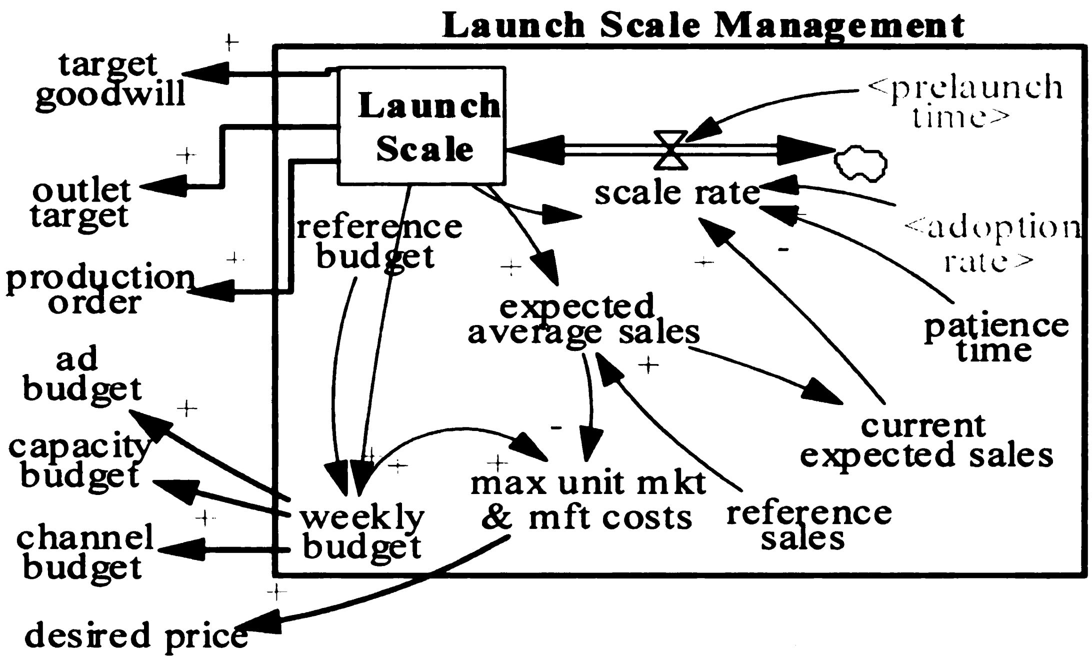
The dynamic launch strategy is based on the dynamic launch model (see Figure 3-25), which is exactly the same as the basic model, except for the launch management module (see Figure 3-26). In the basic model, the new product launch scale is *exogenous*, implying static launch strategies. In the dynamic launch model, the new product launch scale is *endogenous*, implying a dynamic launch strategy based on changing market conditions (which is caused by actual market responsiveness). Specifically, the launch scale is modeled as a stock variable, which is adjusted based on the ratio of *adoption rate* to current *expected sales* and is delayed by *patience time*. That is, the launch policy (i.e., the launch scale) is adjusted in order to reduce the gap between the current expected sales and the adoption rate. For example, if the adoption rate is lower than the expected sales, the launch scale is reduced by a percentage that reflects the difference between the current expected sales and adoption. The reduced launch scale will be lower than the *planned* launch scale and resource commitment for the new product launch. The variable "patience time" models the fact that managerial decisions are usually latent, due to factors such as information delays, managers' patience and confidence with their prior judgments on the market conditions for the product launch, organization inertia, etc. In addition, the formula also makes sure that launch scales do not change before product launches and that the values for the launch scale are within the region of [0, 1]. The current expected sales is a function of time and expected average sales (*current expected sales = 10+ramp(expected average sales/300, 12, 800)*, which implies that the expected sales rate is assumed to start at 10 and reaches the expected average sales at week 300)[10].

Figure 3-25 The Model



[10] This is a simple way to model the facts that managers expects the new product sales increases as time goes by. In reality, the function form should be a non linear one. However, the linear function form is sufficient for the current use in the model, as this only provides a moving reference to be compared with real adoption rate.

Figure 3-26 Launch Scale Management



<u>Scenario #1: High Market Responsiveness</u>

Figure 3-27 demonstrates the dynamic changes in launch scale over time, which starts from the initial medium value of 0.5, quickly exceeds the launch scale for the fat launch strategy (i.e, 0.8), reaches the maximum launch scale 1 at week 82, and stays there until week 200. Finally, launch scale slowly decreases, as the adoption rate reaches its peak and also starts to decrease (see Figure 3-28).

Figure 3-28 compares the adoption rates of the dynamic launch strategy with the fat and narrow launch strategies. The figure shows that the dynamic launch strategy, under high market responsiveness, enables the new product diffusion to take off much faster than it does in both of the static strategies. Furthermore, during the launch time period (i.e., from week 12 to week 300), the unit costs (see Figure 3-29) of the dynamic launch is similar to those of the fat launch strategies and much lower than those of the narrow launch strategies, and the unit costs achieved higher total profits (see Figure 3-30) than those of both of the narrow launch strategies.

Figure 3-27 Launch Scale

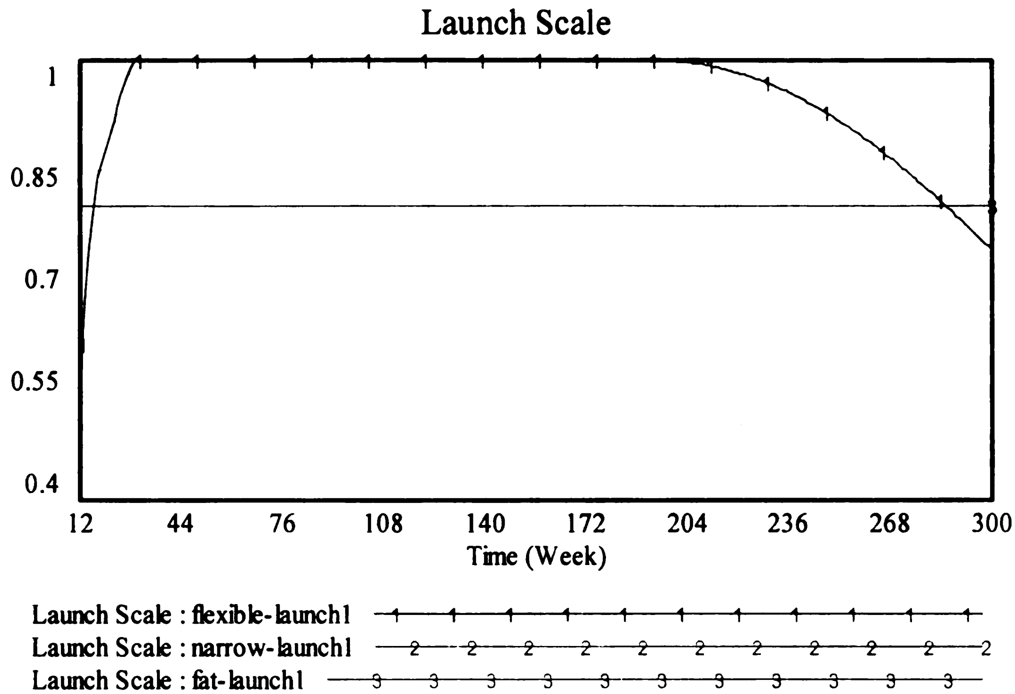


Figure 3-28 Adoption Rate

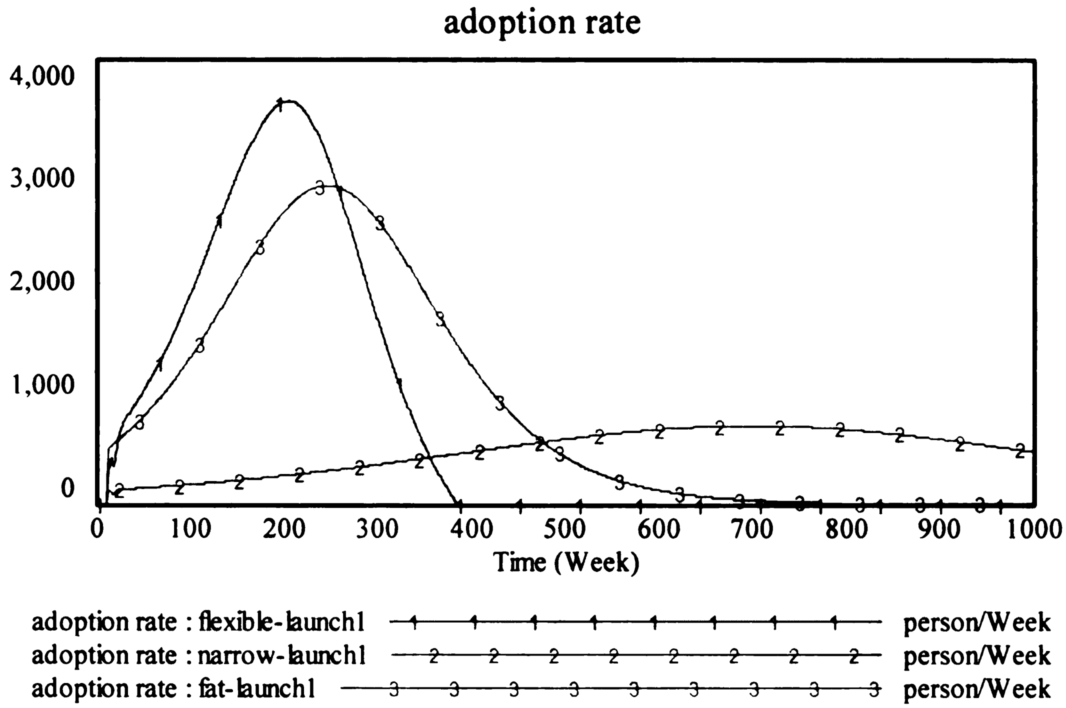


Figure 3-29 Total Profit

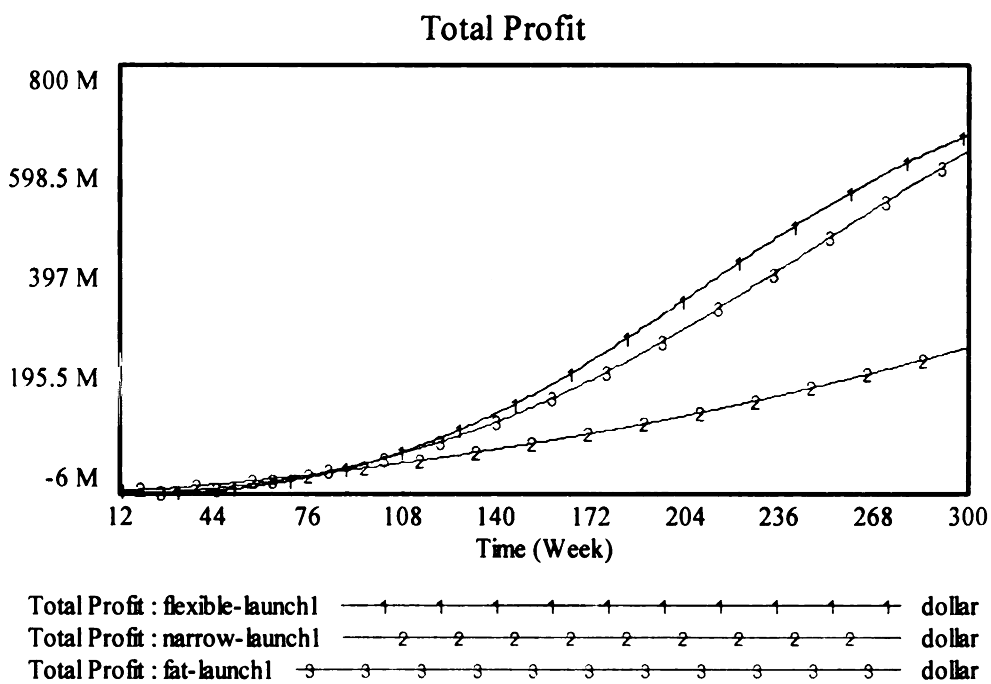
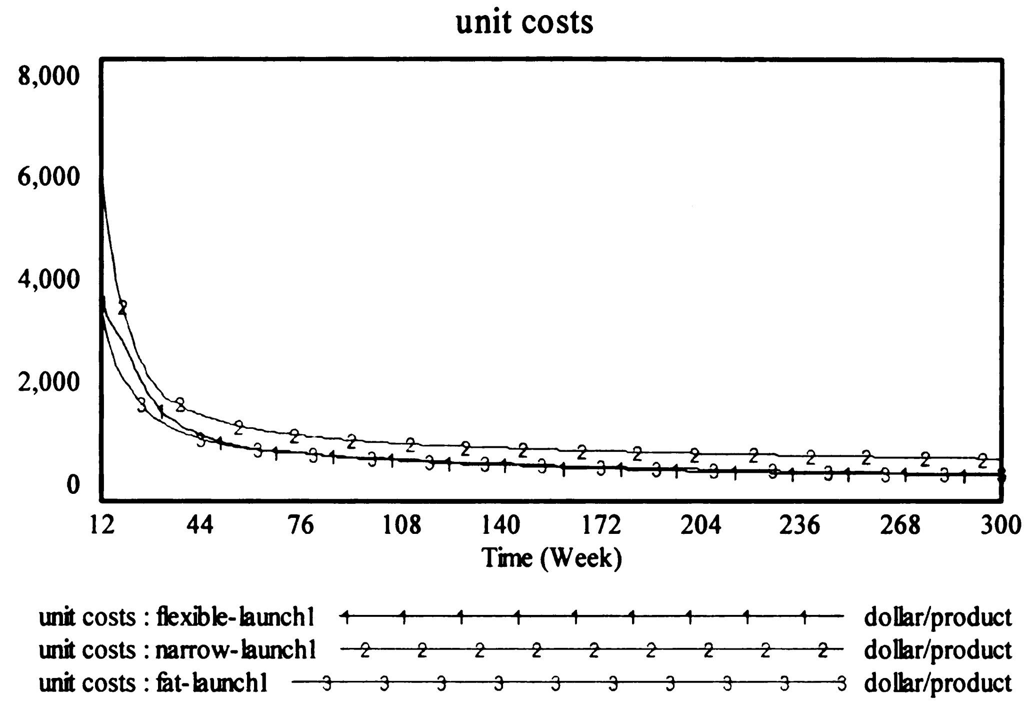


Figure 3-30 Unit Costs



As the launch scales dynamically change, they affect the weekly budgets see Figure 3-31) for the marketing and manufacturing activities that support the new product launch. Following the launch scale, weekly budgets increased dramatically at the beginning of the product launch and decrease at the end of the product launch period.

Meanwhile, market price (see Figure 3-32) for the new product is reduced from more than $2000 to less than $1500, a difference that increases the potential demand for the new products. Similarly, the target for customers' goodness (see Figure 3-33), and the target for retail outlets (see Figure 3-35) are also dynamically changed by launch scales.

Combining a higher weekly budget and high market responsiveness, higher target goodness, and outlet targets leads to much higher actual demand for the new product at the early stage of the new product launch. (For the actual customer's goodness and channel coverage, see Figure 3-34 and Figure 3-36). With a higher product launch scale and a higher weekly budget, both production capacity (see Figure 3-37) and production rates (see Figure 3-38) are increased greatly, which results in larger inventory deployment (See Figure 3-39) and thus to a higher fulfill rate for the demand for the new products. Later on, when the adoption rate slows down, launch scale was dynamically adjusted, and thus, reduced any unnecessary new resource commitment for the new product launch at that stage.

Figure 3-31 Weekly Budget

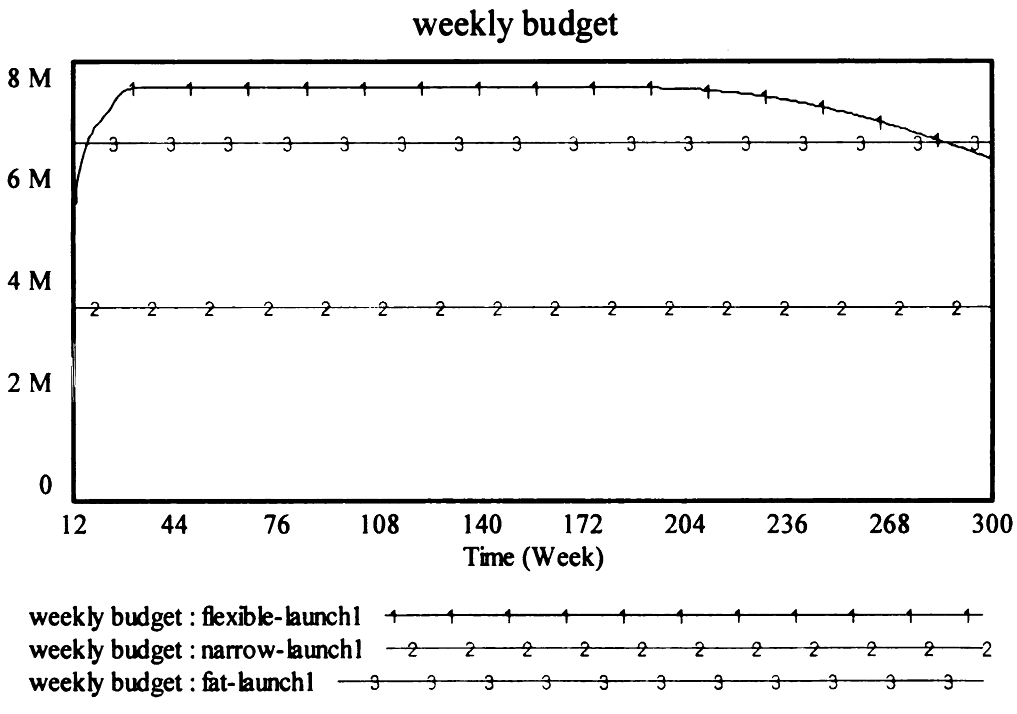


Figure 3-32 Market Price

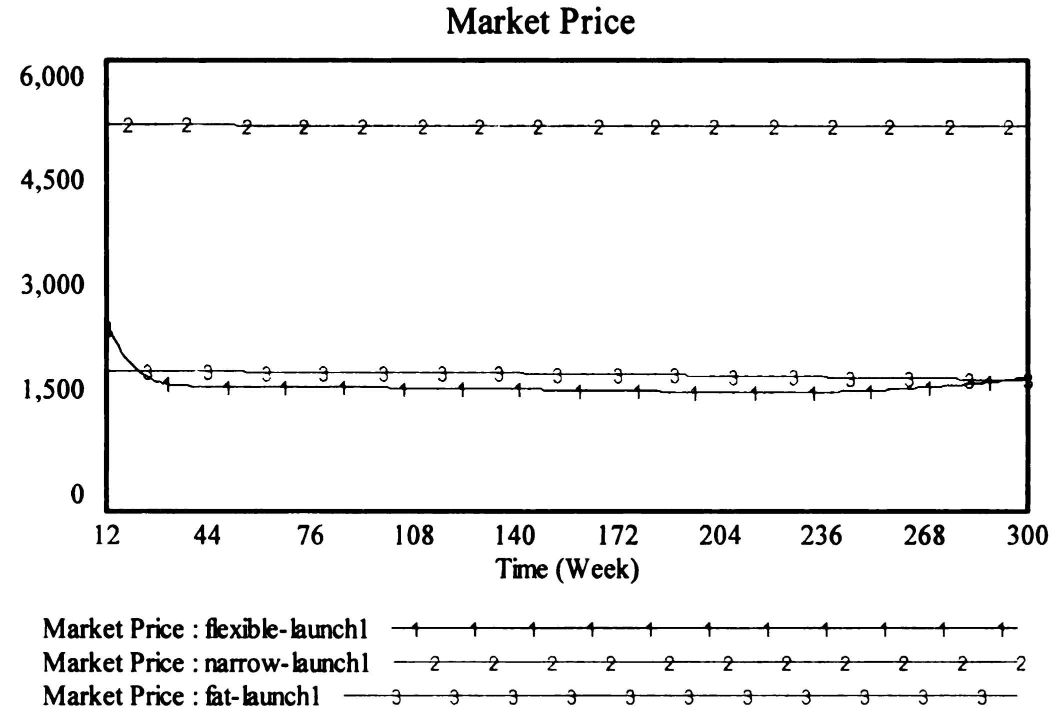


Figure 3-33 Target Goodwill

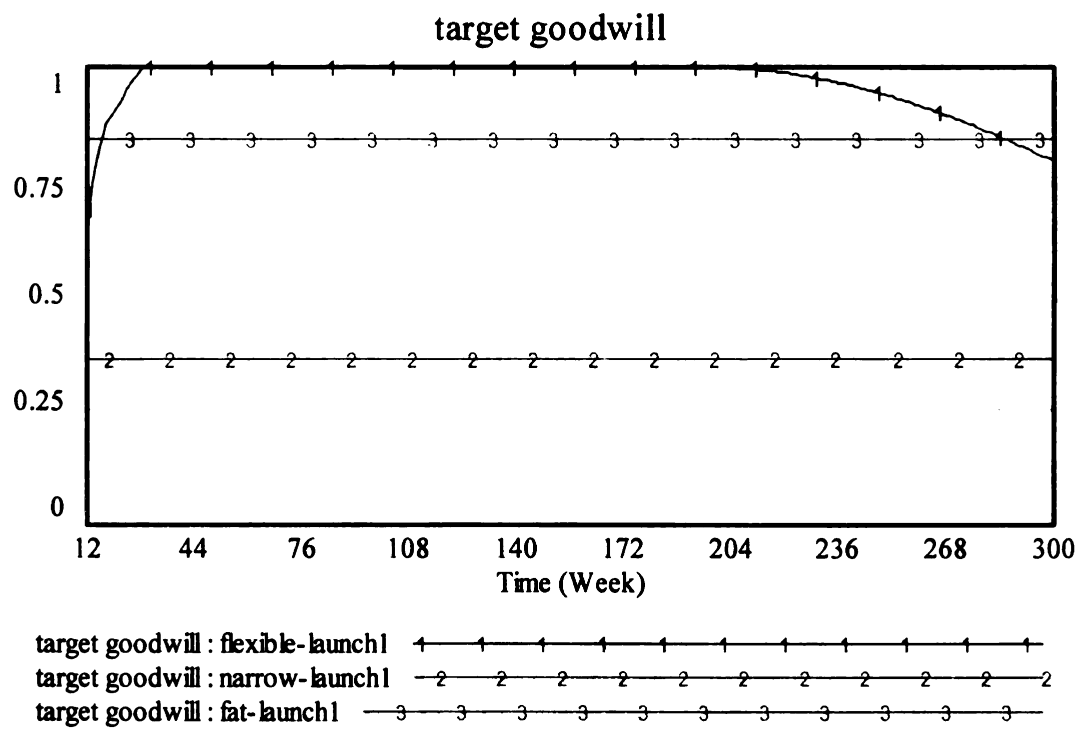


Figure 3-34 Customer's Goodwill

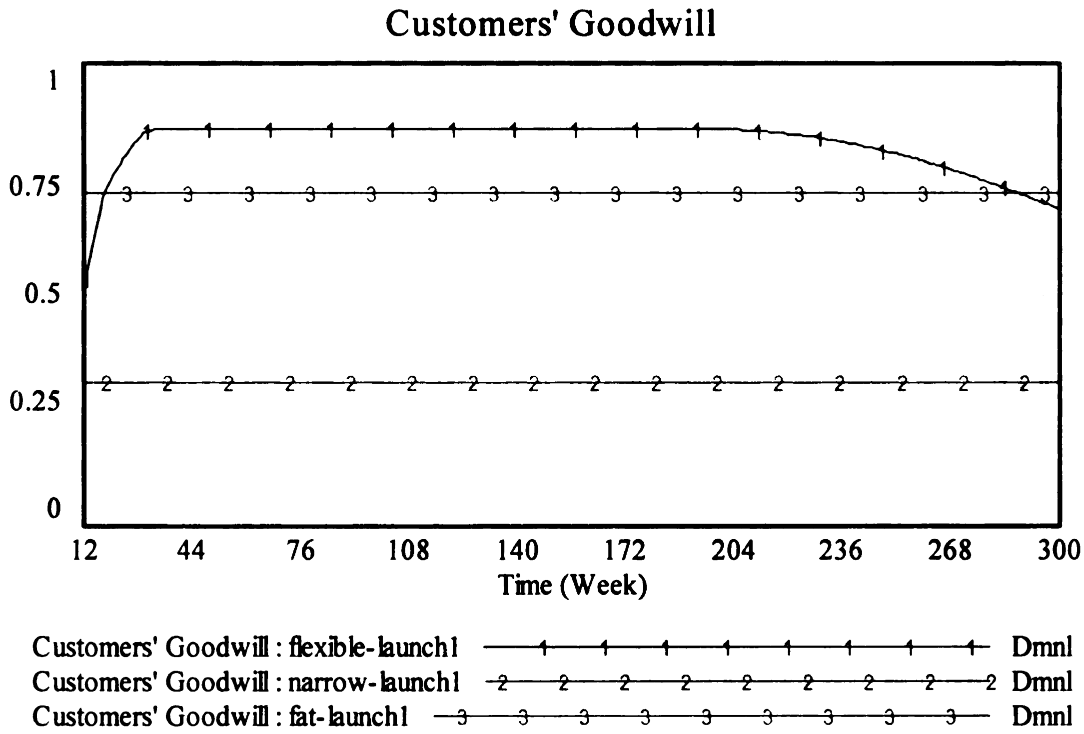


Figure 3-35 Outlet Target

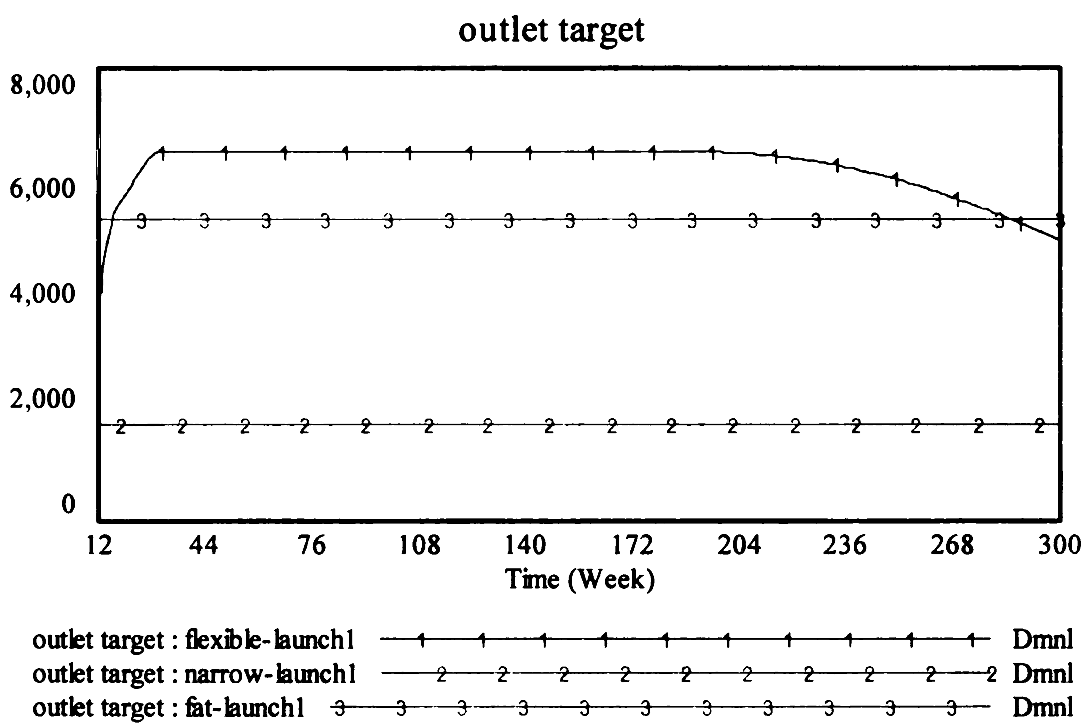


Figure 3-36 Channel Coverage

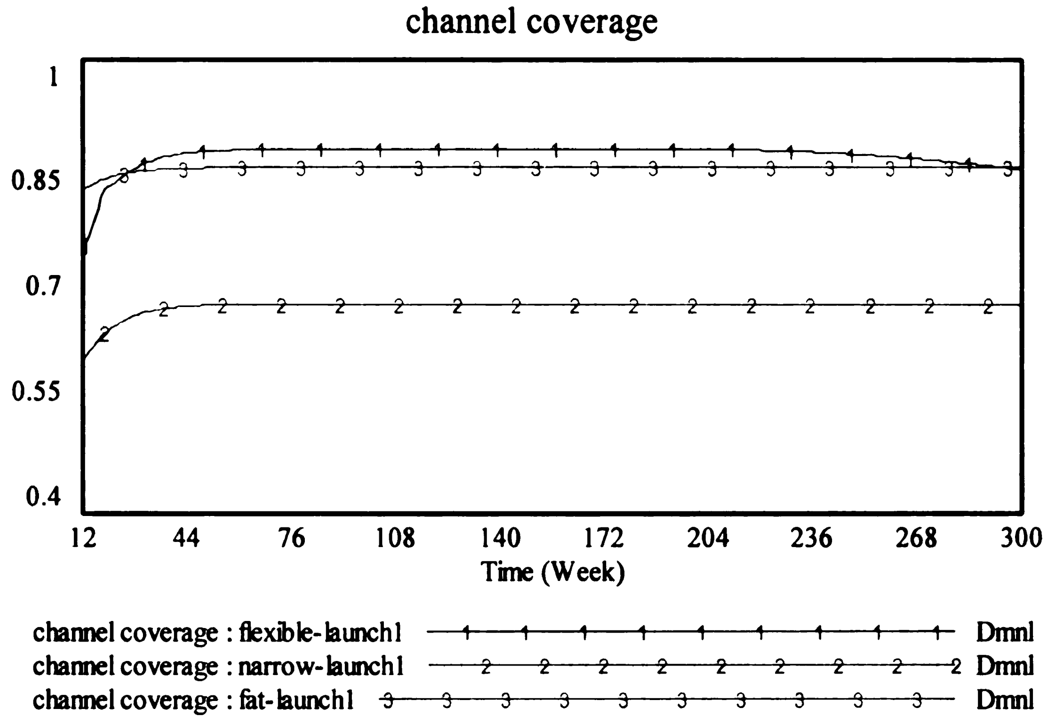


Figure 3-37 Production Capacity

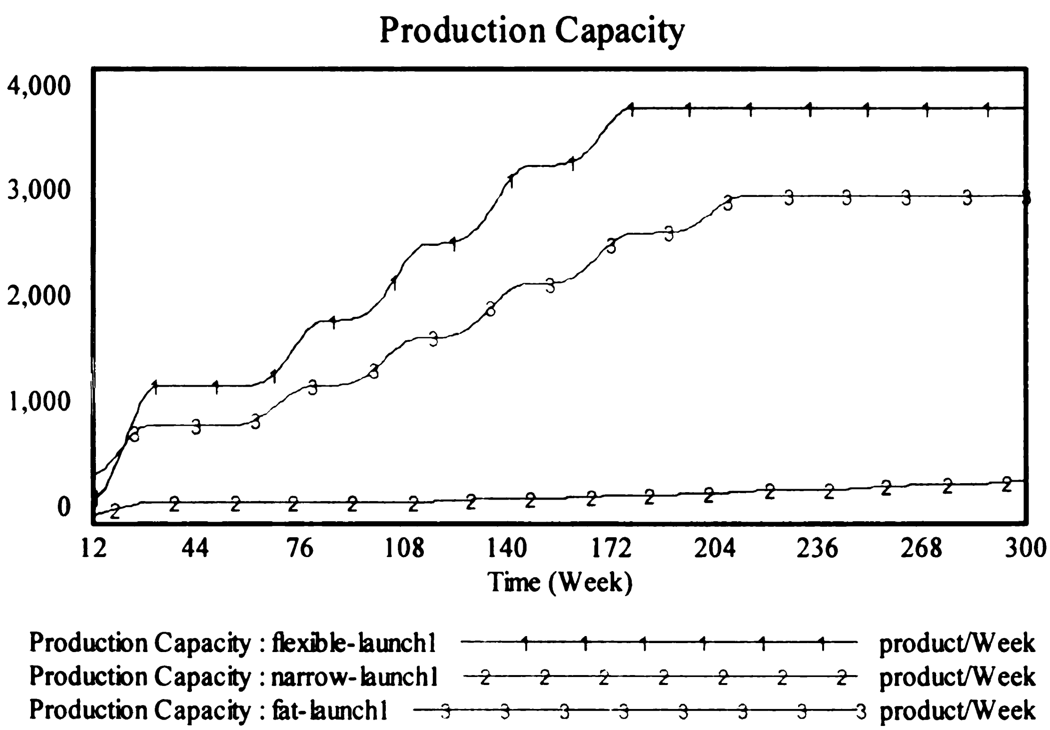


Figure 3-38 Production Rate

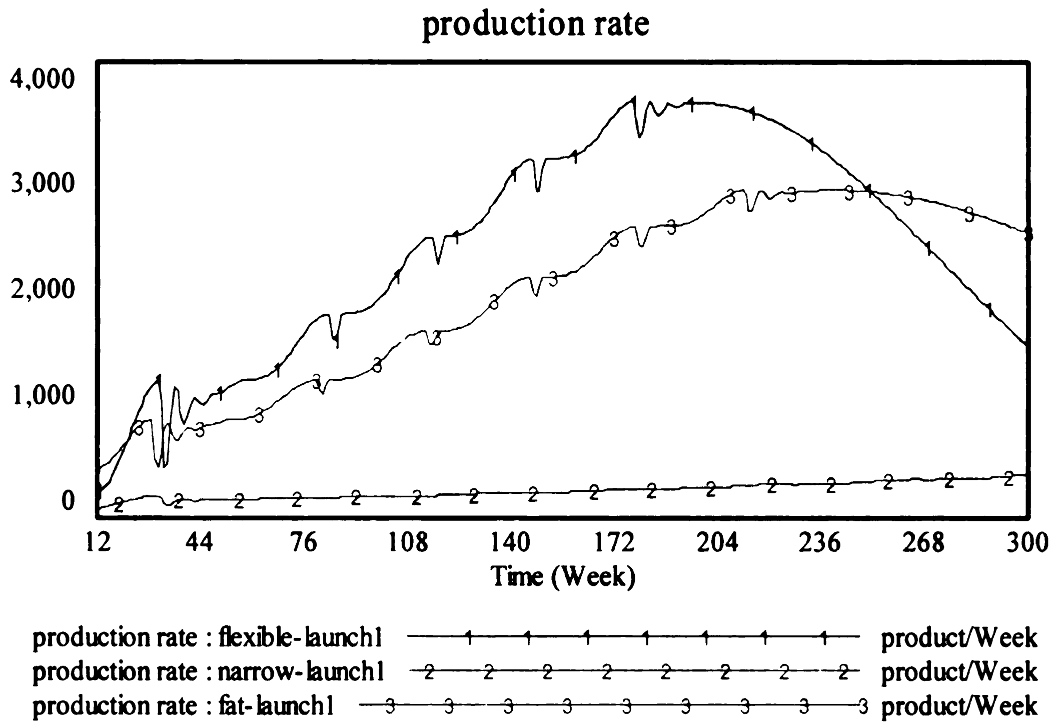
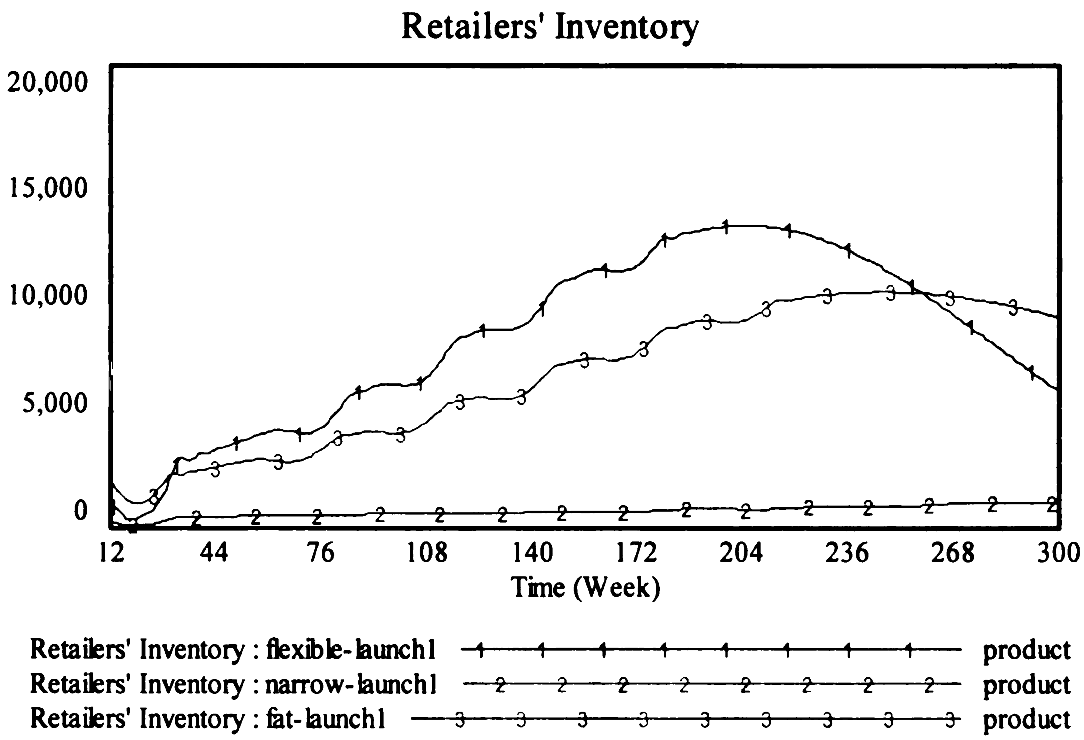


Figure 3-39 Retailers' Inventory



Scenario #2: Low Market Responsiveness

When the market responsiveness is low, the dynamic launch strategy is able to adjust its launch scale quickly to lower values and thus to smaller resource commitment to the new product launch (See Figure 3-40) to match the actual adoption rate (See Figure 3-41). As a result, at the end of the product launch period, the dynamic strategy is able to achieve higher total profits (See 3-42) than both of the narrow launch strategies, even though its initial launch scale is much larger.

The new product's unit costs (See figure 3-43) for the dynamic strategy is between those of the narrow launch and the fat launch, and adopts similar prices at the beginning of the launch. However, the dynamic strategy is able to detect unfavorable market conditions, and so the dynamic strategy quickly increases its prices (see Figure 3-44), thus reducing unnecessary resource commitment to the new product's prices. At the same time, the dynamic strategy is able to adjust its resource commitments to advertising (See Figure 3-45), channel coverage (See Figure 3-46), production capacity (See Figure 3-47), production rate (See Figure 3-48), and inventory deployment (See Figure3-49).

Figure 3-40 Launch Scale

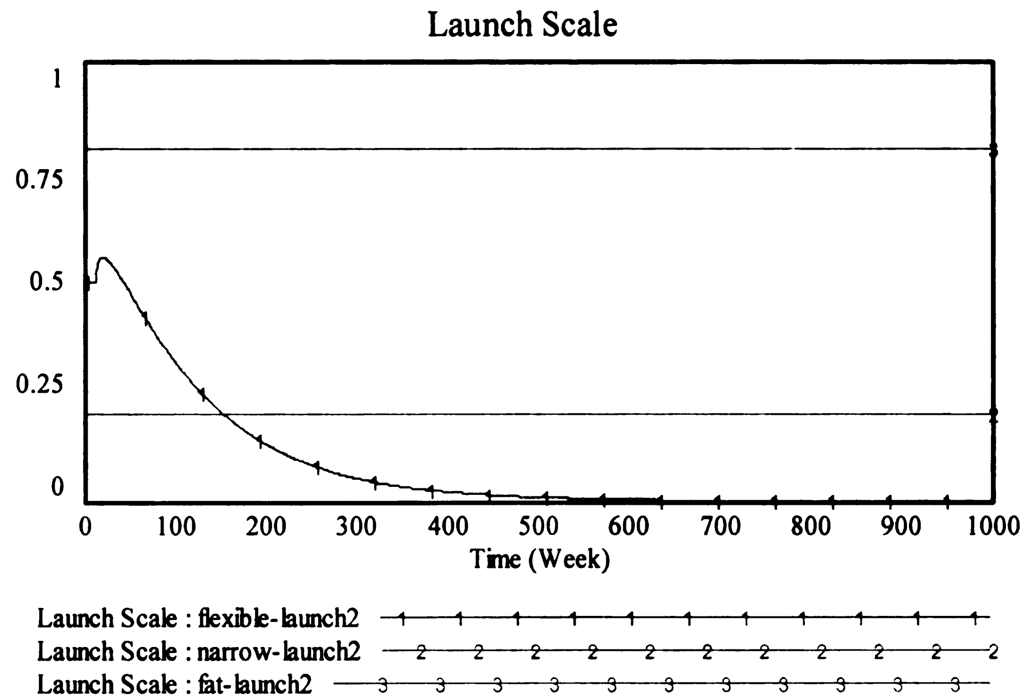


Figure 3-41 Adoption Rate

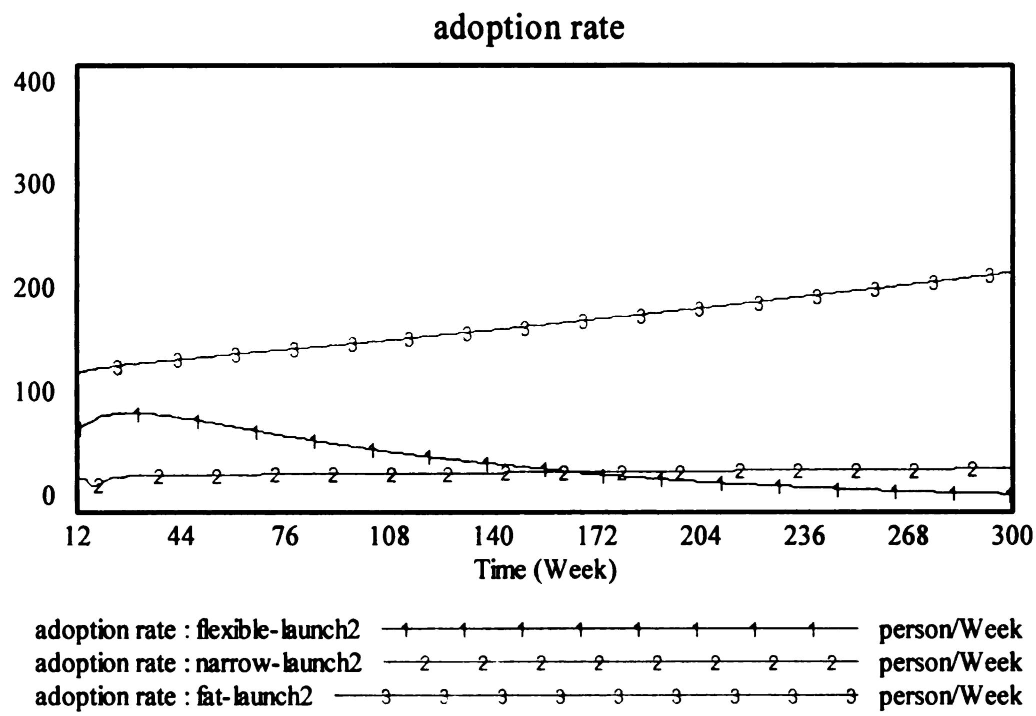


Figure 3-42 Total Profit

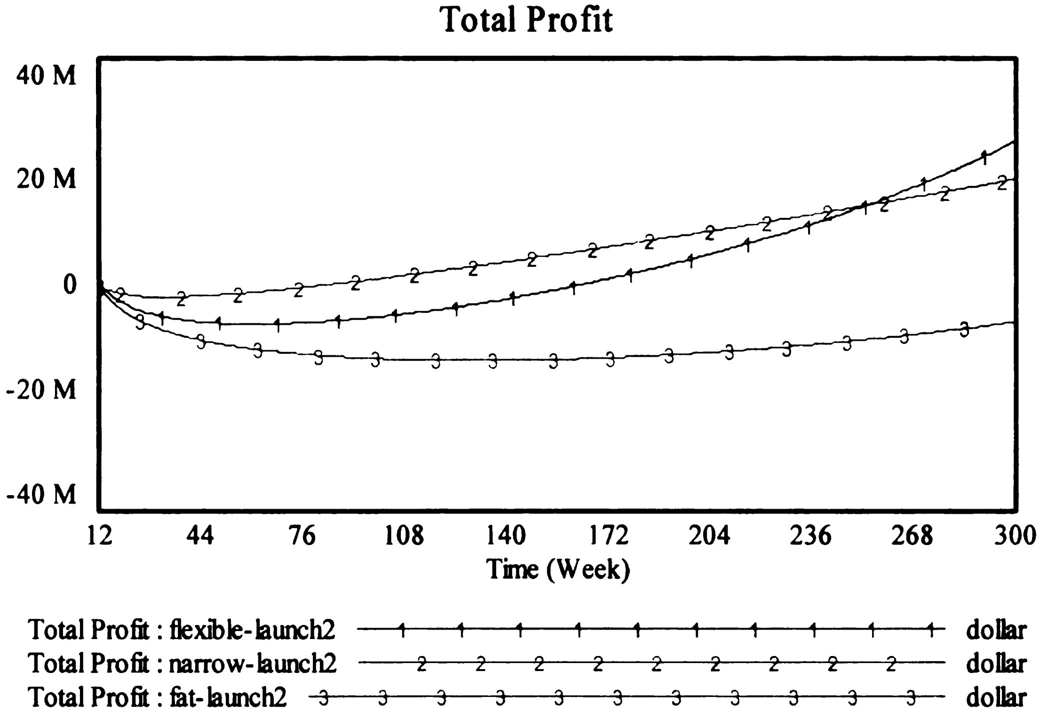


Figure 3-43 Unit Costs

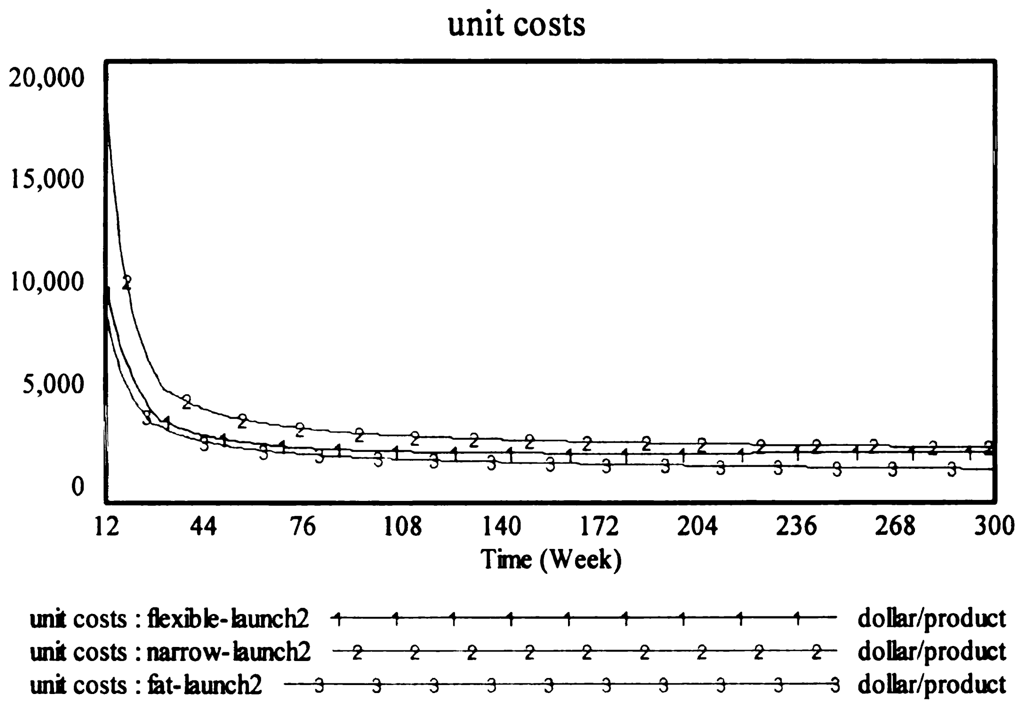


Figure 3-44 Market Price

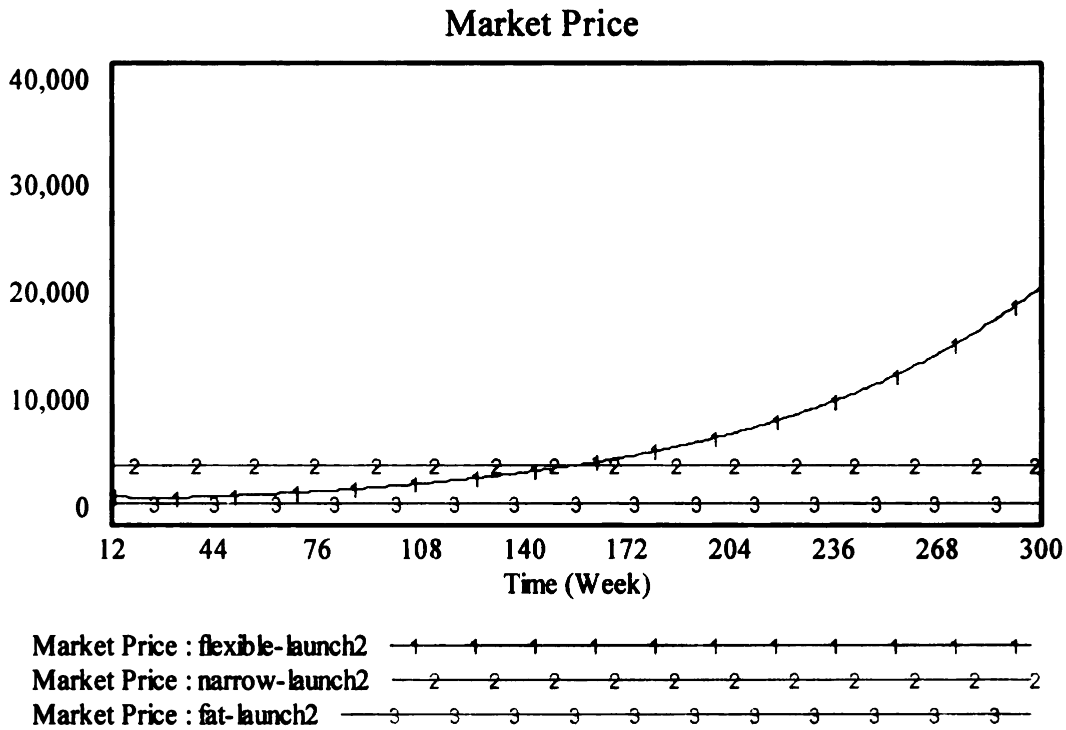


Figure 3-45 Customers' Goodwill

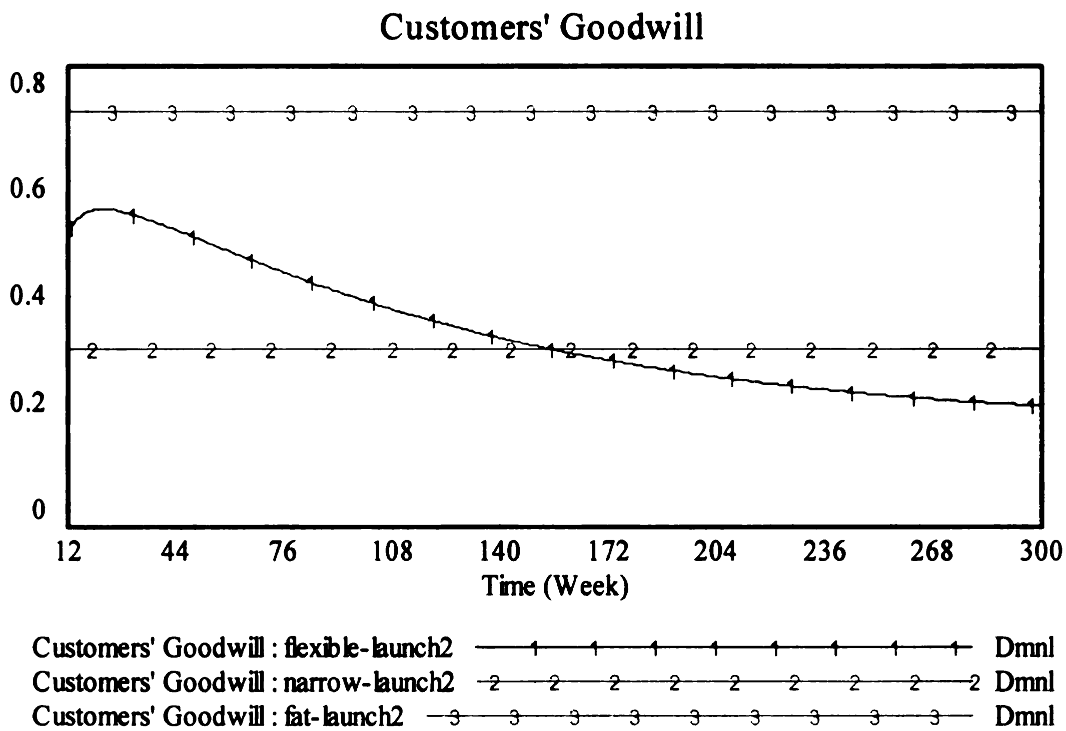


Figure 3-46 Channel Coverage

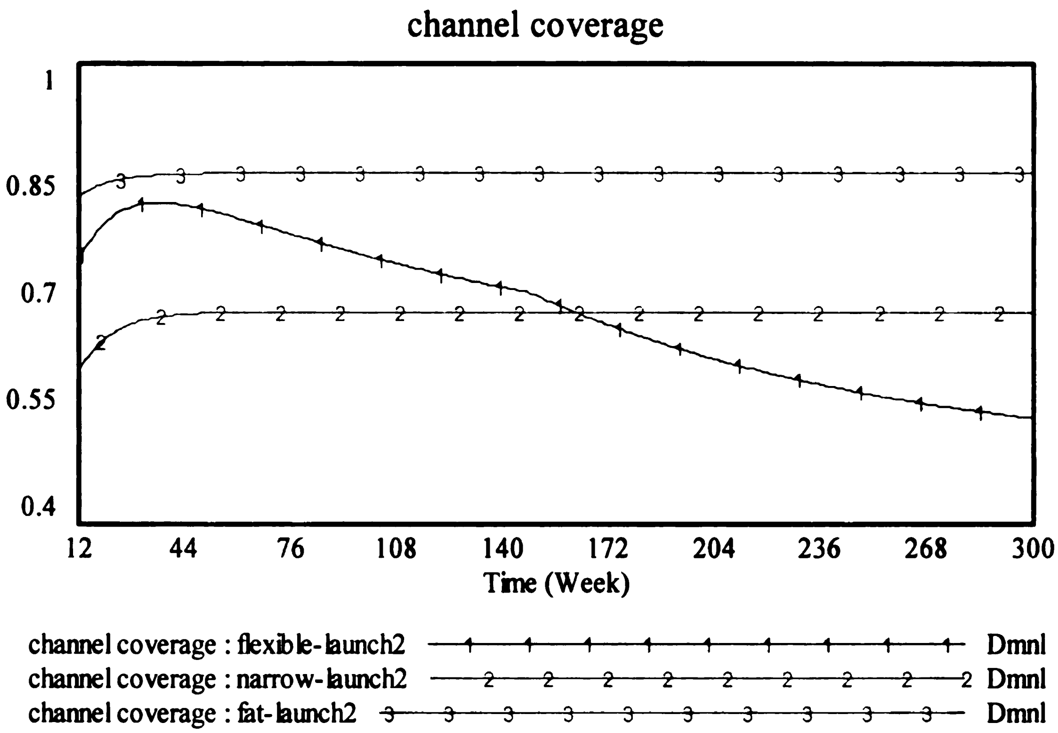


Figure 3-47 Production Capacity

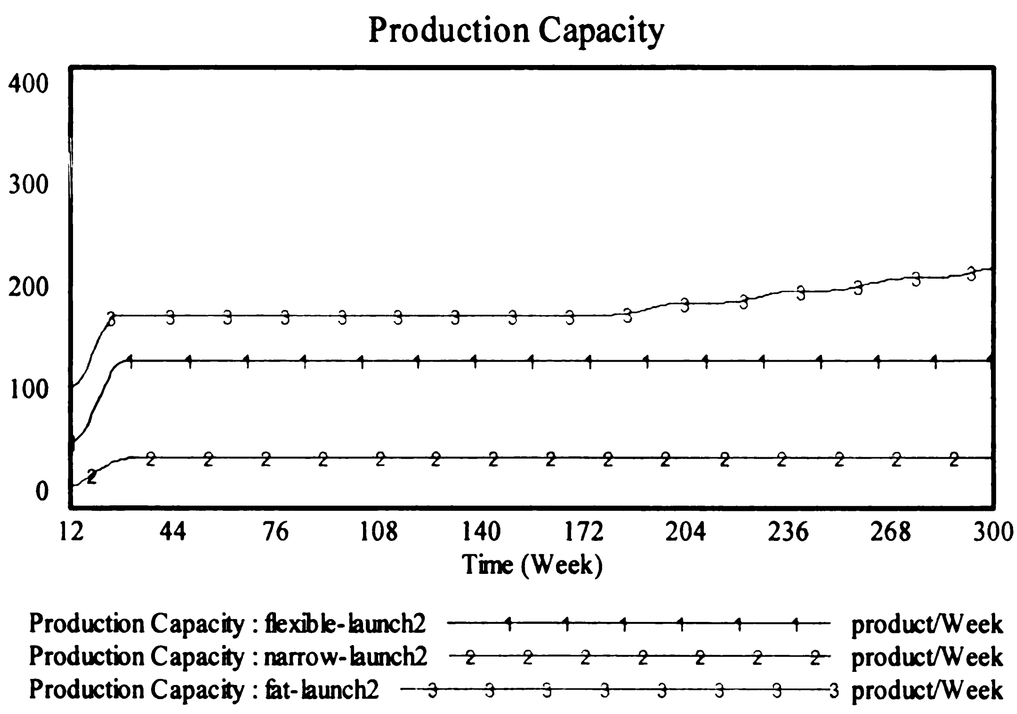


Figure 3-48 Production Rate

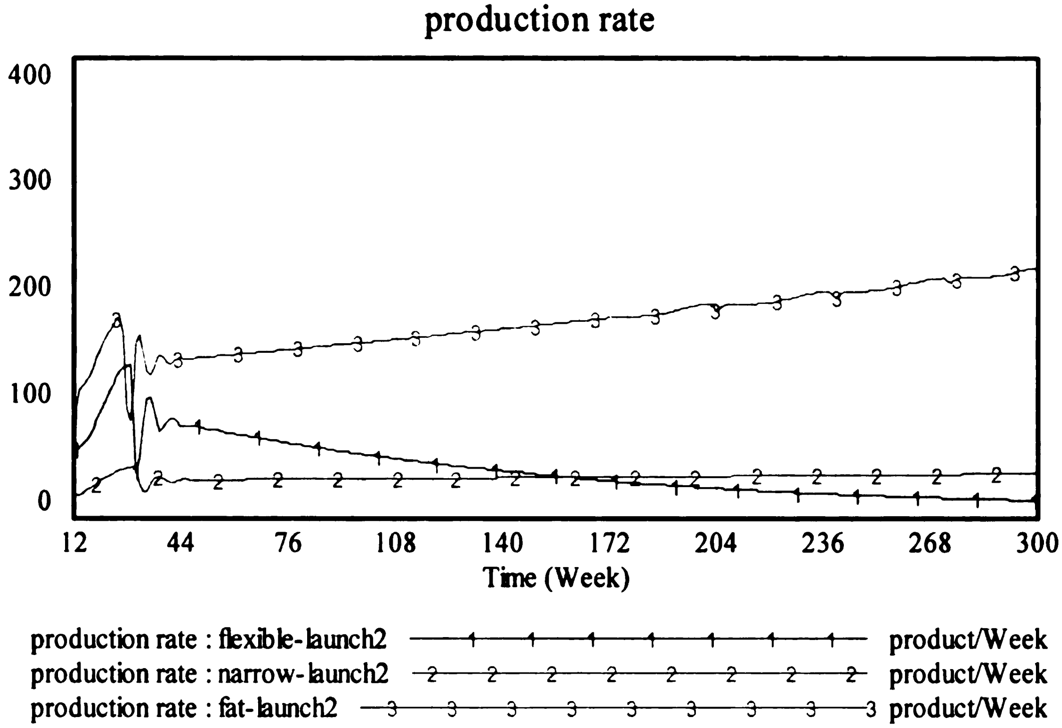
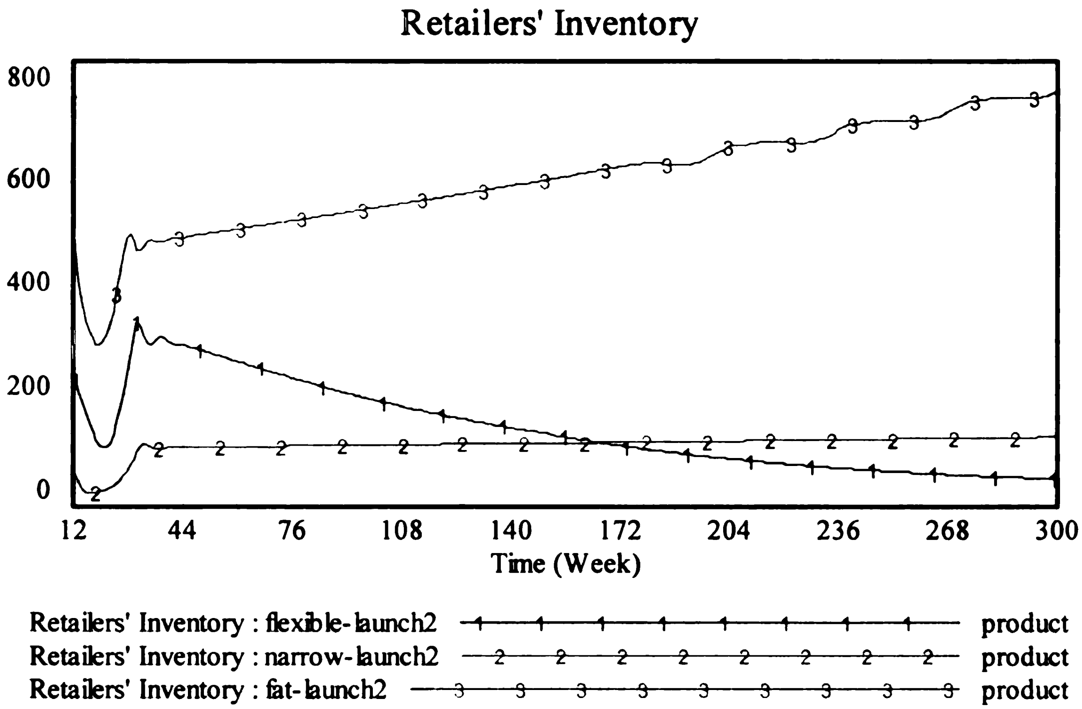


Figure 3-49 Retailers' Inventory



The Effects of Initial Launch Scale

By definition, a dynamic launch strategy dictates that the launch scale is endogenous and is being changed according to the market conditions (in this study, that is, the adoption rate) during product launches. On the other hand, the initial launch scale is exogenous, and is decided by the new product managers based on their pre-launch expectation/speculation/forecasts regarding the demand for the new product.

As shown in the previous sections, the selection of the appropriate initial launch scale is critical to the fate of a new product launch. However, since the dynamic launch is shown to be able to adjust to unexpected market conditions, does initial launch scale matter?

In this section, the effects of the initial launch scale are examined under the scenarios of high and low market responsiveness. Figure 3-50 shows the adjustment launch scales of fat (i.e., high), medium, and low levels of initial launch scales under high market responsiveness. Even though the strategy with the high initial launch scale is one that fits the market condition best, the strategy featuring the medium launch strategy is able quickly to catch up and behave almost the same as the strategy with the high initial launch scale.

However, the launch strategy with the low initial launch scale fails to fully take advantage of favorable market conditions and does not capture as much market demand (See adoption rates in Figure 3-52), and profits (see Figure 3-51) as the other two strategies do. This difference among the three types of launch scales demonstrates that accurate pre-launch forecasts and correct selection for the initial launch scales are still very important for creating a dynamic launch strategy. However, the dynamic launch strategy is robust enough to alleviate the mistakes in pre-launch forecasts and in initial launch decisions associated with high market uncertainties, especially if the initial launch scale is not too far away from the actual market conditions.

Figure 3-50 Launch Scale

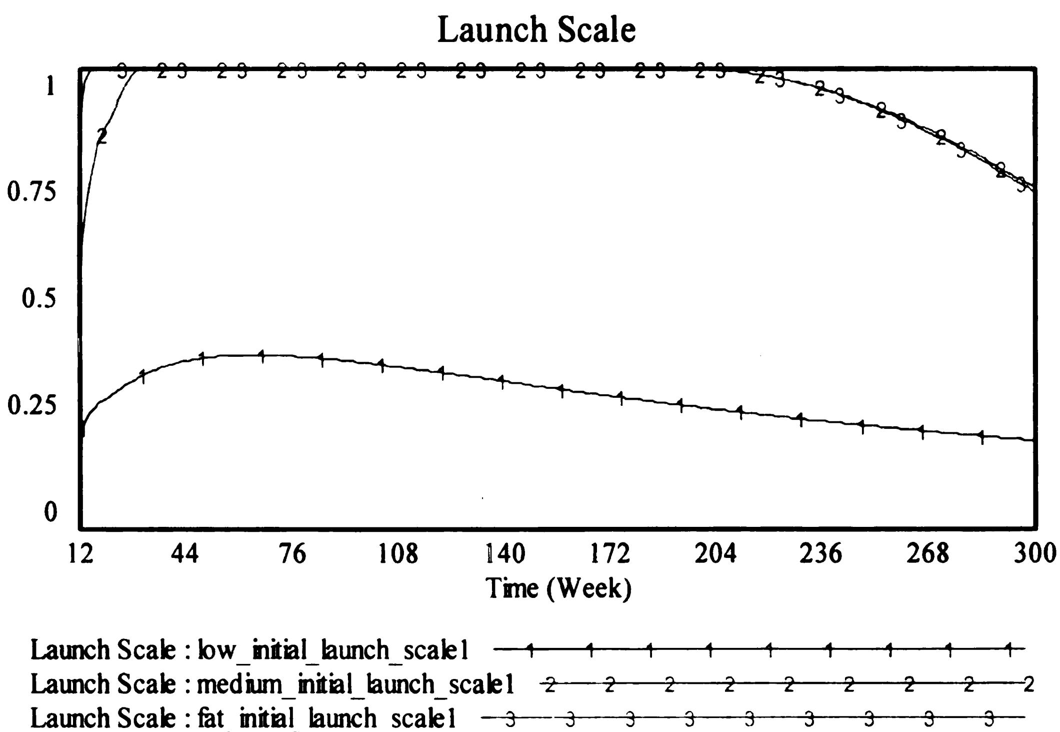


Figure 3-51 Total Profit

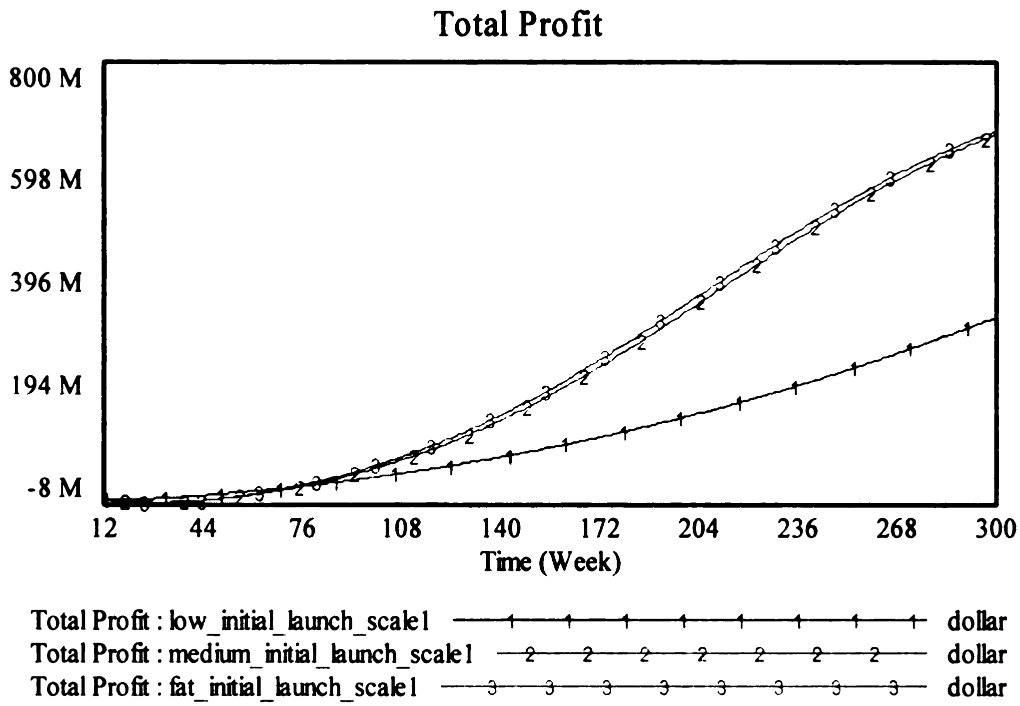
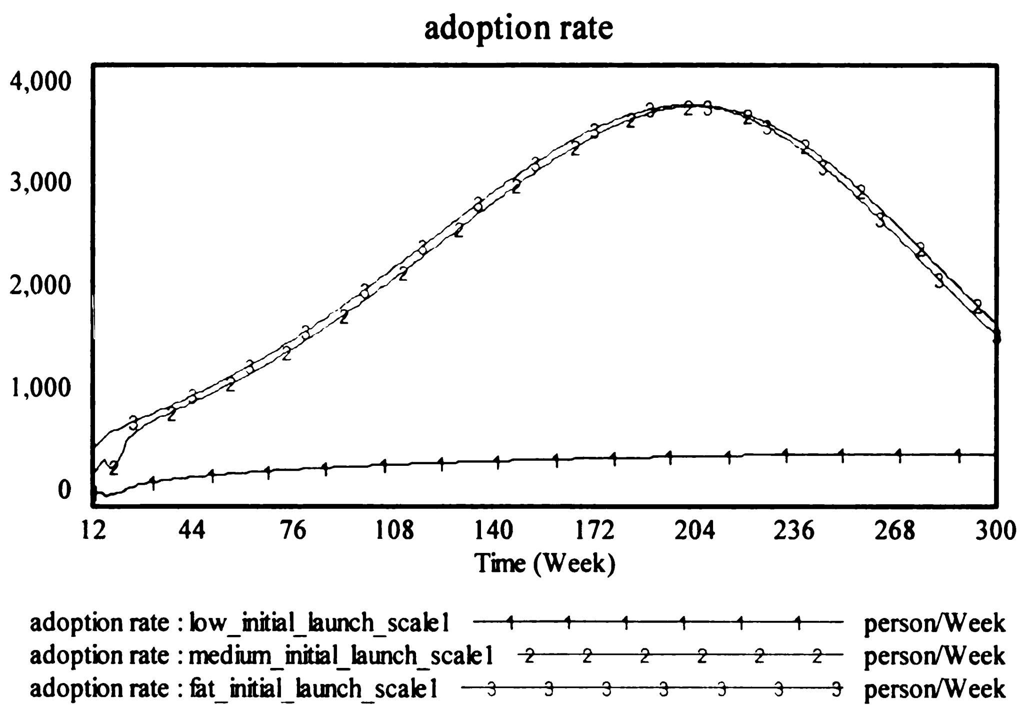


Figure 3-52 Adoption Rate



The robustness of the dynamic launch strategy is also supported under the condition of the low market responsiveness. Figure 3-53 shows how dynamic strategies featuring different levels of initial launch scales adjusted to unfavorable market conditions. All of them were able to quickly lower their resource commitments to the new product launch, and thus reduce unnecessary costs. Because of the different levels of sunk costs at the initial stage of the product launch, the higher the launch scale, the lower total profit (See Figure 3-54) the launch strategy achieved at the end of the new product launch. Even though higher initial launch scale leads to relatively higher adoption rates (See Figure 3-55), the difference is too small to recover from the effects of wasteful commitment at the initial stage of the launch.

Figure 3-53 Launch Scale

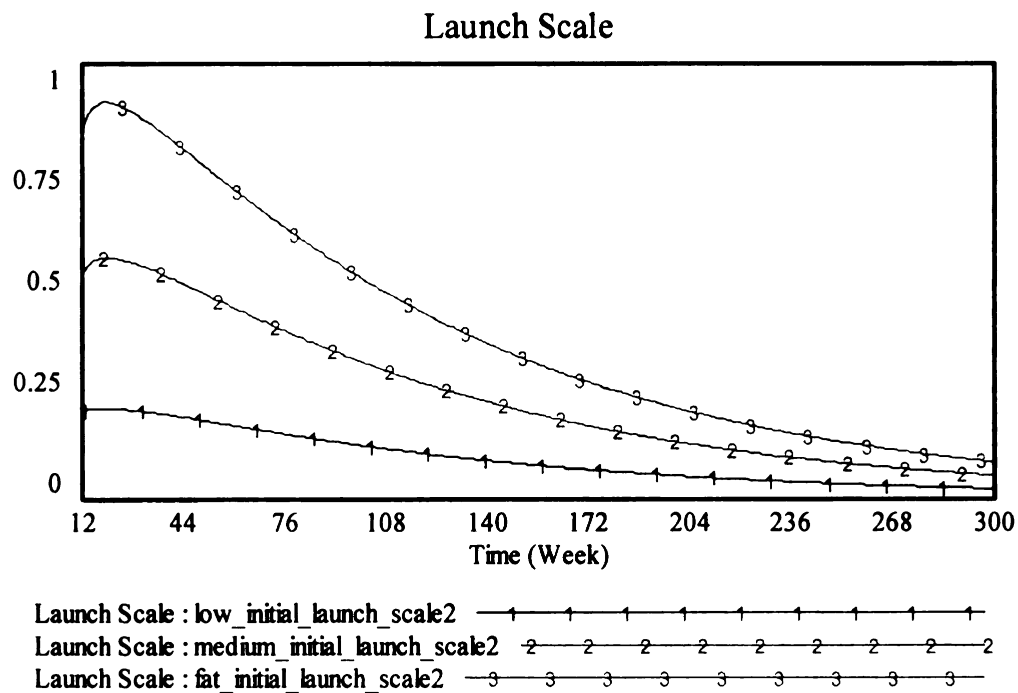


Figure 3-54 Total Profit

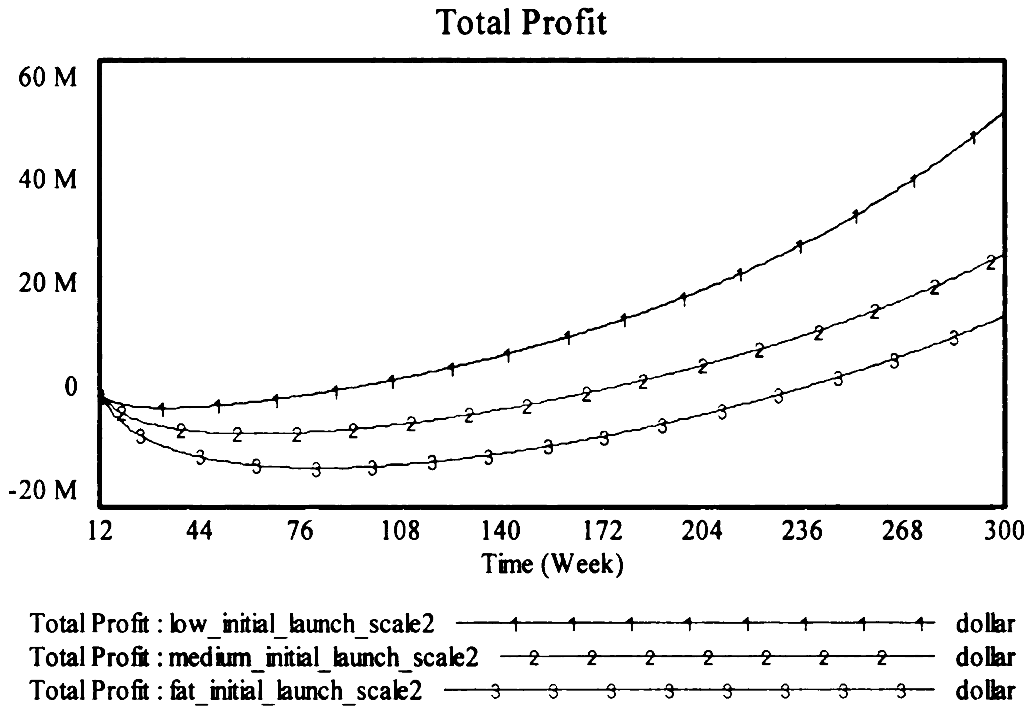
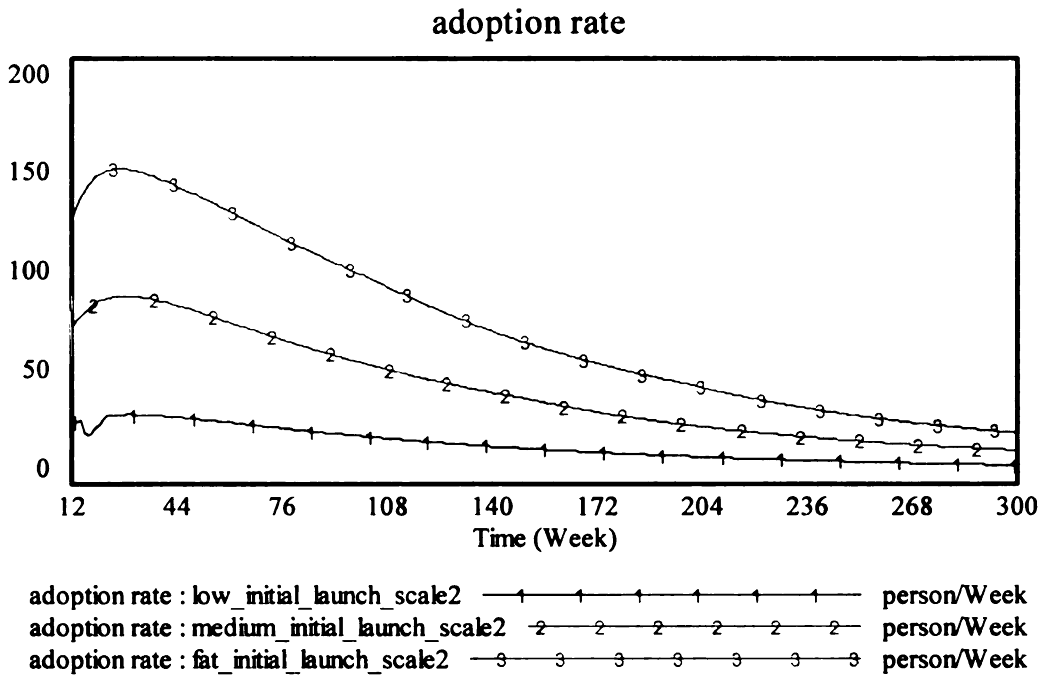


Figure 3-55 Adoption Rate



Findings for the Dynamic Launch Strategy (The Dynamic Launch Model)

The results from the dynamic launch model support the central theme of this study, that is, that under high market uncertainties, new product managers must adjust their launch strategies dynamically according to market conditions in order to achieve superior performance for new product launches. Specifically, there are several key findings associated with the dynamic launch model:

Finding #4: The dynamic launch strategy is superior to static launch strategies, as it can dynamically adjust its resource commitments to match changing market conditions.

Finding #5: The pre-launch market forecast is still an important factor in dynamic launch strategies because better selections of initial launch scales lead to better launch performance.

Finding #6: Unlike static launch strategies, the dynamic launch strategy is more robust in response to a poor pre-launch forecast associated with market uncertainties, as it can quickly move away from its initial launch scale and can adapt to the actual market conditions.

Discussion

Theoretical Contributions

From a theoretical standpoint, this study makes and accomplishes several important contributions. First, it proposes and tests an integrated product launch strategy framework that incorporates both the marketing and the supply chain management perspectives. It also provides a holistic view regarding how to manage various product launch tactics such as pricing, advertising, channel development, production and inventory management.

Second, this study addresses ways in which market uncertainties can be managed for new product launches, which are intrinsic to new product launches, but are largely neglected in new product literature.

Third, this study investigates market launch strategies not only from a marketing perspective, but also from a supply chain perspective, perspectives which are considered as keys to launch successes, but which are often neglected.

Fourth, the study introduces a new concept – product launch scale - which reflects the resource commitments a firm makes to a New Product Development (NPD) project. It demonstrates that launch scale is the key to integrating various launch tactics, reconciling a firm's long term policies and short-term policies toward an NPD project, and dealing with market uncertainties associated with new product launches.

Fifth, the study demonstrates that traditional new product launch strategies work only when the market uncertainly is low and market forecasts meet the actual market conditions. However, under high market uncertainties, traditional new product launch strategies are rather inefficient and can be costly, as they are unable to cope with unexpected market conditions.

Sixth, new product launch policies at the tacit level is rather ineffective in optimizing the new product launch process, which can only be optimized through launch policies at the strategic level, that is, at the product launch scale.

Seventh, dynamic launch strategies, which adjust their launch scales according to actual market conditions, work much more efficiently than do traditional static launch strategies.

Finally, even though dynamic launch strategies are still based in part on good pre-launch market forecasts, the dynamic launch strategies are more robust than are those with poor pre-launch forecasts associated with market uncertainties because a strategy can quickly move away from its initial launch scale and adapt to actual market conditions.

Methodological Contributions

This study has also made some important mythological contributions to both the field of new product development and the field of the system dynamics method. First, it has successfully developed and validated a first-of-its–kind system dynamics model that incorporates several interacting dynamic processes: a new product diffusion process, a marketing response model, and a supply chain management model (i.e. ordering fulfillment, inventory management and manufacturing model). The resulting model provides several key building blocks toward developing a more complicated system dynamics model to study new product management using the system dynamics approaches.

Second, this study provides a new approach for modeling the new product launch process. The new approach enables researches to understand the new product launch process from a dynamic perspective, instead of from the traditional static perspective.

Third, this study develops an innovative approach to modeling both the static and the dynamic natures of a firm's resource commitment toward a new product launch.

Managerial Contributions

This study provides several important strategic insights on managing market uncertainties for new product launches. First, in order to achieve efficient and successful new product launches, it is critical for firms to develop integrated launch policies at the strategic level, which should incorporate not only marketing tactics such as advertising, channel and distribution, pricing, etc.; but also supply chain management tactics such as inventory management, order management, and manufacturing management. Tactical policies alone are ineffective for optimizing product launches or managing market uncertainties.

Second, dynamic launch strategies always work better than do static launch strategies, because they allow firms the flexibility of making adjustments at the strategic level based on actual changes in market conditions. Therefore, it is critical for firms to employ dynamic launch strategies when market uncertainties are high.

Third, the product launch scale (i.e., resource commitment for a product launch) should be used as the key strategic lever for new product launches. It offers a simple but powerful tool for viewing the new product launch process holistically and for integrating various launch tactics into a coherent strategy.

Fourth, even though dynamic launch strategies can alleviate high market uncertainties, pre-launch market prediction still matters. That is, dynamic launch strategies should only used as a safeguard for potential false market predictions due to high market uncertainties. Firms must still pay attention to market research and strive for its accuracy.

Future Research

This study offers several potential research directions for extending this study. First, the market uncertainties modeled in this study are rather simple. More complicated models of market uncertainties should be introduced to test the robustness of the models discussed in this paper and this researcher's findings. Second, the scenario used in the model implementation is based on a hypothesized product and its marketing and supply chain. Even though the hypothesized product, its demand, and its marketing and supply chain fit very well with classical textbook scenarios and are suitable for use in the current study, it would be interesting to implement and calibrate the model based on a real-world product launch. Such an implementation might reduce the parsimoniousness of the model and increase this study's generalizability, but it might also provide some interesting applications for practitioners. Third, the model can also be used as a "flight simulator." That is, managers/trainees could be provided periodically with data on key state variables of the model so that they could then make decisions on launch scales and launch tactics accordingly. Then the model might provide feedback to the managers for their next round of decisions. The "flight simulator" approach can provide two interesting applications: one would be use as a managerial training tool for new product managers. The other would be to use the human feedback data to further calibrate the model and make it more realistic. Fourth, the model can be further studies with the dominant loop analysis (Kim 1995; Richardson 1995), which is helpful in analyzing relationships between dynamic system behaviors and close loop structures. By identifying the conditions of dominant loop shifts, and the dynamic roles that those key feedback structures play, this exercise has the potential to provide further insights on the mechanism of how a new product launch process is affected jointly by market conditions, and various marketing and supply chain strategies.

CHAPTER 4
THE WEALTH EFFECTS OF INNOVATION ANNOUNCEMENTS, NEW PRODUCT ANNOUNCEMENTS AND NEW PRODUCT LAUNCHES: A HIERARCHICAL PERSPECTIVE

Introduction

An important concern in marketing theory is the relationship between marketing strategy and shareholder value (Day and Faahey 1988; Srinivasan and Bharadwaj 2004). However, the focus on micro-level tactical issues has led to concerns that marketing's strategic role is steadily shrinking (Day 1992). The key concern is marketing's failure to demonstrate value relevance (such as stock market valuations) in terms that matter to senior management (Sheth and Sisodi 1995).

This study attempts to fill the theoretical gap by investigating the relationship between new product development (NPD) strategy (i.e., NPD announcements) in marketing and its related shareholder values. Specifically, the study deals with the stock market's responses to announcements at different stages of a new product development (NPD) project. In financial and accounting literature, the stock market's response to an announcement is called a wealth effect, which is defined as a firm's stock price differences before an announcement and after the announcement of that firm. In this study, three types of NPD announcements are investigated: 1) *innovation* announcements, 2) *product* announcements, and 3) *launch* announcements. An innovation announcement is defined as the event when the focal firm deliberately signals to the market that it is developing or has developed key technologies for a new product project. A product announcement is defined as the event when the focal firm deliberately signals to the market about its intention to launch (i.e. commercialize) a new product in the near future. A launch announcement is the event when the focal firm actually launches the new product.

The purposes of the study is 1) to understand various factors that affect the relative sizes of wealth effects for the three different types of NPD announcements; 2) to investigate the linkages among the three sequential wealth effects, and 3) to determine ways in which to optimize the wealth effects before the actual product launch and thus be able to use the positive wealth effects to offset potential new product launch risks.

The paper is organized as follows: presented first, is a review of all relevant literature review; second, research gaps are identified; third, research questions are raised and research hypotheses are developed; fourth, the research methodology is discussed; fifth, the collected data is analyzed and the results are presented; and finally, the results are discussed.

Literature Review

Several streams of literature that are related to the current research are identified: 1) literature on the event study methodology (which investigates wealth effects of events) and its roots in finance, accounting, economics and strategic management literature; 2) event studies in the field of marketing; 3) the literature on R&D activities (which is related to the NPD) and firm performance, the literature on NPD announcements, and the literature on the wealth effects of NPD announcements .These streams of literature will be reviewed in the following sections.

Literature on Event Studies

The majority of event studies are conducted in the fields of finance (for integrated reviews, see Brown and Warner 1985; for integrated reviews, see Fama 1976; MacKinlay 1997) and accounting (for an integrated review, see Kothari 2001). These studies are primarily interested in testing the market efficiency hypothesis (MEH), which examines security price performance either over a short window of a few minutes to a few days (short-window tests) or over a long horizon of one-to-five years (long-horizon tests). The events of interests are usually such things as earning announcements, other accounting and finance related events, and macro-economical events. Usually, after testing the MEH, a cross-section regression is conducted by regressing the abnormal returns on some characteristic specific to the events or observations.

Event studies are also used in the strategic management literature (e.g. Koh and Venkatraman 1991; e.g. Lubatkin et al. 1989), which often deals with events such as the formation of joint ventures, mergers, divestitures, diversifications, product-market interventions, executive successions, strikes, etc. Lubatkin and Shrieves (1986) have noted that researchers in finance tend to view corporate events quite differently than do researchers in strategic management: finance views incorporate events such as mergers in discrete, tactical terms rather than as an outcome of a series of related events. Lubatkin and Shrieves recommend that researchers in strategic management make adjustments to event studies on the selection of the time frame, sample frame, appropriate statistical methods, and proper benchmark of normal returns when calculating abnormal returns.

Event Studies in Marketing

Traditionally, the marketing literature has been primarily focused on how to manage marketing based assets (such as customer relationships and partner relationships) to achieve customer satisfaction and loyalty, which, in turn, lead to faster market penetration, product price premiums, lower sales/service costs, etc (Srivastava et al. 1998). Srivastava et al. argue that such market-based phenomena can also increase shareholder value through accelerating cash flows, enhancing cash flows, reducing volatility and vulnerability of cash flows, and enhancing residual value of cash flows. In an integrated review, Srinivasan and Bharadwaj (2004) have identified a very limited number of event studies in marketing: 1) the effects of a corporate name change (Horsky and Swyngedouw 1987), 2) new product introductions (Chaney et al. 1991), 3) brand extensions (Lane and Jacobson 1995), 4) joint ventures (Houston and Johnson 2000), and 5) the addition of an Internet distribution channel (Geyskens et al. 2002). Even though these studies have consistently indicated that various marketing strategies and functions have a significant initiative-to-shareholder value, the event study methodology has not been in widespread use in marketing (Srinivasan and Bharadwaj 2004).

Literature on R&D Activities and Firm Performance

The growth of R&D expenditures over the last two or three decades, together with the continuous substitution of knowledge capital for physical capital in firms' production functions, has elevated the importance of R&D in the performance of business enterprises. The ability to evaluate the risk and eventual payoffs from corporate R&D is therefore of considerable importance to capital market practitioners and researchers. The evaluation of R&D activities is seriously impeded, however, by antiquated accounting rules and insufficient disclosure by corporations (Lev 1999).

There are primarily three approaches to empirically investigating R&D and its impact on the stock market. 1) The first approach is to use survey data to relate R&D inputs (intensity, capital) to firms' productivity, sales, or profits growth in an attempt to estimate the return on corporate investments in innovation-producing activities. However, this approach suffers from many problems, the most obvious of which is that the time lag between investments in R&D and the realization of benefits is generally unknown and is often long, thereby increasing uncertainty about the estimated regression parameters. 2) The second approach is to use patent data (such as patent counts and citations) as R&D output (for a review see Griliches 1989; Hall et al. 1998). This approach has proved useful and valid by numerous researchers such as Deng and Lev (1998), Trajtenberg (1990), Shane (1993), Hall et al. (1998), etc. This approach is most useful to assess a firm's long-term R&D potential. 3) The third approach is to use event studies to study the capital market values (i.e., the investors' reactions) to new R&D initiatives (e.g., Chaney and Devinney 1992; e.g., Chaney et al. 1991; Chen and Ho 1997; Chen et al. 2002; Kelm et al. 1995).

Existing Literature on Wealth Effects of NPD Announcements[11]

An NPD announcement is defined as a firm's formal and deliberate signaling of intended future actions (1995). In the marketing and strategic management literature, the announcement is regarded as a strategic communication tool, which can be used to elicit desired reactions from the firm's buyers, suppliers, investors, competitors, channel members, industry observers, and influencers. Schatzel (1999) divides the announcement literature into five categories: 1) content (restricted to "typical" future marketing actions, and less studied); 2) timing (the degree to which the communication is issued in advance of the intended action); 3) target audience, such as competitors, buyers, and investors; 4) channel of communication; and 5) intensity. The existing literature does not provide a clear categorization of announcements at different stages of new product development.

A survey[12] of the existing literature on wealth effects of NPD announcements has resulted in 7 articles demonstrating a wide range of research sophistication (Chaney and Devinney 1992; Chaney et al. 1991; Chen and Ho 1997; Chen et al. 2002; Eddy and Saunders 1980; Kelm et al. 1995; Pardue et al. 2000). Generally, the unit of analysis is the announcement event. Most studies first tested the market efficient hypothesis with event studies

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[11] As noted earlier, previous literature does not make any distinction between the innovation announcement and the product preannouncement. Therefore, the term pre-announcement will be used to represent all types of new product announcements before a product launch.

[12] The literature search was first conducted with the key word "product announcement," "product pre-announcement," and "product introduction" from both the Web Science Social Science Index, and Proquest database. Those articles that deal with stock market reactions have been selected from the results. This researcher has used the Web Science Social Science Index's cross-reference function. Those articles that had cited the selected articles and those articles being cited by the selected articles are also examined in this work.

methodologies. Then, researchers generally pooled all the events and conducted a cross-section regression test by regressing abnormal returns on some industry-specific or firm-specific variables. The findings suggest that abnormal returns are influenced by both firm-specific and industry-specific variables, such as firm size, investment opportunities, competitions, R&D intensity, etc. (For a detailed review, please see Table 1). In addition, most of those studies implicitly or explicitly regard announcements as the proxy for the focal firms' R&D and new product development activities, not as the deliberate signaling from the focal firms.

Table 4-1 Summary of Stock Market Reactions to Announcements

Article	Unit of Analysis	Sampling Frame	Data Sources	Sample	Method for Calculating Abnormal Returns	Dependent Variable	Independent Variables	Findings
Chaney et al. (1991); Chaney & Devinney (1992)	Announcement of new product introduction	Wall Street Journal Index from 1975-84 on new product introduction, excluding auto and airline industries, joint ventures, new contracts of a non-unique nature.	CRSP & COMPU-STAT	1101 announcement by 231 firms	The market model is estimated from -600 days to the beginning of the event window. The abnormal returns are estimated based on four different event windows: (-1,1), (-3, 3), (-5, -1), and (-5, 5).	Abnormal returns	Beta (the risk of the firm), number of product announcements made over the 10-year period, single- vs. multiple- product announcement, whether the product is an update of an existing product, a firm's assets, profitability and R&D expenditures, industry dummy variable, interest rate	The value of a new product announcement is the greatest for the most technologically based industries. Original new product introduction clearly dominates reformulated or repositioned existing products.
Kelm et al. (1995)	Innovation announcement & new product commercial-ization announce-ment	Wall Street Journal Index from 1997 through 1989; announcement in the categories of biotechnology, new products, science & research, & technology	CRSP & COMPU-STAT	197 innovation announcement & 304 commerciali -zation announcement in 23 industries	Market model (based on equal valued CRSP Index) parameters are estimated from -120 to -21 days before announcement & the abnormal returns are estimated from -1 to day 0.	Abnormal returns	Industry R&D intensity, relative firm R&D intensity, industry concentration, relative firm growth rate, firm size, frequency of announcements, and moderator: stage of project	Project stage moderates the relationship of technology and market (firm and industry) variables to the wealth effects of $& project announcements.

Chen & Ho (1997)	Announcement of Product Strategies and capital expenditure	Singapore-listed industrial firms from 1983 to 1991; announcements from the Daily Financial News	Financial statement Daily Financial News, and SES	87 product-strategy announcement by 45 firms; 77 capital-expenditure announcement by 44 different firms.	Market model (based on value weighted SES All-Share Index) parameters are estimated from -200 to -60 days. Abnormal returns are estimated from -1 to day 0.	Abnormal returns	Tobin's q (the proxy of a firm's investment opportunities; and cash flows	Tobin's q is significant, while cash flow is not.
Chen et al. (2002)	Announcement of new product introduction	Searches on key words such as "introduce," "new product," "unveil," launch," "received approval," "to market," "test market," begin selling," etc. from Dow Jones News Retrieval Services Database	CRSP & COMPU-STAT	384 new product announcement by 101 firms in 39 industries	Market model (based on value weighted CRSP Index) parameters are estimated from -200 to -60 days. Abnormal returns are estimated from -1 to day 0.	Abnormal returns	Strategic competition, investment opportunities, free cash flow, debt ratio, firm size, R&D intensity, high or low technology industry stock of patents, announcement frequency, single vs. multiple-product announcements, interest rate	Firms competing in strategic substitutes have a positive announcement effect, but those competing in strategic complements have non-significant announcement effects. Strategic competitions have negative effects on the wealth effects of product introduction announcements

Pardue, Higgins et al. (2000)	New product announcement (excluding announcement regarding product availability, or volume production)	Hard drive product announcement in PR Newswire, Predicast, ABI/Inform, and the Wall Street Journal Index from 1981 to 1994.	CRSP, Institutional Brokers' Estimate System (IBES) tape (for earning forecast data)	58 announcement	Market Model parameter is estimated from -250 to -1 days. The abnormal returns are estimated from -1 to day 1.	Abnormal returns; abnormal earning forecast	Eras of technical advance: era of ferment vs. era of incremental technical change, competition with existing dominant design vs. competition with emerging technology	The announcement causes negative market reaction to the firm's new product. The market reaction to the firm's announcement in terms of either the era of technical advance or type of competition is non-significant, although, analysts' reactions are significant.

Research Gaps in Previous Literature

Based on the literature review above, several research gaps are identified:

1. **Unit of analysis.**

   Most (if not all) of the research studies in the above streams of literature are either at the firm level or at the event level. For NPD research, it is more appropriate to use projects as unit of analysis.

2. **Announcement at different states of NPD projects' life cycle.**

   Most of the research (except Kelm et al. 1995) has failed to considered NPD announcements' wealth effects in the context of the stages of the NPD projects at the time of the announcement. As Kelm et al. (1995) has suggested, the stock market reacts rather differently toward the announcement at different stages of NPD projects.

3. **The relationship between the wealth effects of two subsequent announcements of the same project.**

   In the context of a new product development project, the wealth effects are not only related to the characteristics of the current events, but also to the previous events (announcements) related to focal new product projects. The reasons are as follows. First, as a series of deliberate signals by a new product project, the previous announcement and the current announcement are highly correlated due to the new product project manager's intended strategic maneuvers. Therefore, the current event and the previous events related to the same new product project cannot be regarded as independent events. Second, the market evaluates reactions to the current event based not only on the new information provided by the current event, but also on the previous information about the new product project, which is provided by the previous event. For example, if the previous announcement about a new product project is highly positive, the current positive announcement of the same project will not generate as much abnormal return as it would otherwise.

4. **Other determinants of the wealth effects**

As Kelm et al. (1995) has noted, previous research on NPD announcements' wealth effects has failed to control the carry-over effect of previous announcements on the same NPD projects' subsequent announcements' wealth effects. As such, the estimation for other factors (such as market, industry, technological and financial factors) is biased.

5. **A product launch as an event**

Previous research only considers market signaling before a product launch, but not the launch itself. As argued earlier, announcements are biased signals on the actual nature of the NPD project. However, product launches are the events in which the NPD project actually reveals itself. Therefore, it would be interesting to examine the relationships between the effects of signaling and the effects of the actual revelation of the new product project.

Research Objectives

Based on the identified research gaps, several research objectives are set up for the current study:

1. Develop a practical classification scheme that categorizes NPD announcements based on the stages of NPD projects
2. Develop a theoretical framework that links the wealth effects of three sequential major events (i.e., innovation announcements, new product announcements, and new product launches) in the new product development process
3. Investigate how various factors affect the wealth effects of NPD announcements at different stages of NPD projects.
4. Develop a data collection method that allows the study to trace the entire life cycles of NPD projects.
5. Extend the existing event study methodology by employing a three-stage simultaneous equation modeling approach.

The Research Hypotheses and the Theoretical Framework

Announcements at different NPD stages

Researchers agree that NPD projects evolve over stages, which are usually linked to each other in sequences, rather than standing alone as isolated events (Contractor & Narayanan, 1990; Fahey & Narayanan, 1986; Kirzner, 1979; Marquis, 1969; Nelson & Winter, 1982; Quinn & Mueller, 1963; Sahal, 1981; Utterback & Abernathy, 1975). Although theoretical models of NPD stages differ with respect to specifics, there is general agreement that during the early phases, a firm is involved in attempts to innovate to find a technical solution to a problem, and that in the later stages, firms are involved in attempts at commercialization. Therefore, we can classify announcements (or events) on NPD projects into three categories: 1) the announcements that indicate new products/innovations are being developed (i.e., innovation announcements);2) the announcements that indicate new products have been developed and are being commercialized (i.e., product announcements); and 3) the announcements that indicate that the products are launched (i.e. launch announcements)[13].

The stock market's valuations of NPD announcements at different NPD stages are rather different (Kelm 1995). First, as an NPD project evolves over stages, information about an R&D project reaches the market gradually, thereby enabling investors to develop and revise expectations about the project over time. The expectation revisions are not solely based on the new event (i.e., the new announcement), but the differences between the previous event (i.e., an NPD announcement at an earlier stage of the same NPD project). The differences are, in fact, the new information, which causes the stock market to

[13] However, it must be noted that, for a particular new product project, the above-defined three events do not all have to occur during the new product's life time. A failed new project might not have a product launch event. Meanwhile, management can choose to forgo the product announcement and the innovation announcement. In this study, no announcement during some stage of a new product project is defined as a "non-event," which is also considered as an event.

generate abnormal returns (i.e., wealth effects) for the current announcement (Fama 1976).

Second, as an NPD project moves further, the risks associated with the NPD project decreases (Cooper 1979; Cooper 1998). Therefore, when investors evaluate the three sequential NPD announcements for a NPD project, they will use different discount rates to calculate the net present value (NPV) of the NPD project. For example, after the initial innovation announcement for a NPD project, the product announcement would indicate a lowered risk level for the NPD project. Thus, if the cash flow expectation is the same for the NPD project, it still implies an increased NPV of the NPD project, which, in turn, would result in a positive wealth effects for the announcement.

Third, investors face different valuation contexts. That is, different NPD stages require an organization's attention to different tasks. For example, at the stage of innovation announcements, the critical tasks are to acquire technical related capabilities and resources. At the stage of product announcement (commericialization), market resources and industrial opportunities are more critical. And when products are launched, financial resources are more critical to for the NPD's successes.

Therefore, this study proposes that the three sequential wealth effects for an NPD project are related. That is, the size of the NPD announcement at later stages is not only determined by the current announcement and the announcing firm's situations, but also by the wealth effects of the previous announcement, which provides a basis for investors to evaluate the current announcement.

Furthermore, the criteria investors employ in valuing the three sequential announcements of a NPD project differ. Specifically, investors emphasize technological issues at the innovation announcement, market issues at the product announcement, and financial issues at the launch announcement.

The Wealth Effects of the Three Sequential NPD Announcements

The financial economics literature suggests that the stock market responds to announcements only when they contain new information that has cash flow implications. For an NPD announcement, there are two types of new information: 1) new information specific to the NPD projects, such as new breakthroughs, new sales and market potential estimations, etc., which varies across projects; and 2) new information that indicates the current stage of the NPD project. Because the first type of new information is project specific and not systematically associated with the three categories of NPD announcements studied here, the new information is assumed to be random across NPD projects. Instead, the second type of new information is systematically associated with the three categories and the NPD announcement by definition, and it only varies across announcement categories.

When investors evaluate an innovation announcement, they usually assign a much higher discount rate for the NPD project than they would when they evaluate a product announcement of the same NPD project, *ceteris paribus* (i.e., the investors expect the same level of cash flow generated from the project, but with a different discount rate[14]). When a subsequent product announcement is made for the same NPD project, it indicates to investors that the project has solved most of the technical issues and that some prototypes or samples have been developed. As the technical risks of the project decrease, the discount rate used to evaluate the project's NPV also decreases and the NPV increases. *Ceteris paribus*, the increased portion of NPV (i.e., the wealth effect of the product announcement) should be proportional to the original size of the NPV[15]. Therefore, the following hypothesis is proposed:

> **H1: The wealth effect of a new product project's innovation announcement has *a positive impact* on the wealth effect of that project's *product announcement.***

The launch announcement of an NPD project indicates that most production and engineering problems for the NPD project have been solved, pre-launch activities have been completed, and the product is being launched to the market, which implies a positive stock market reaction toward the launch announcement. However, the size of the wealth effect is limited by the often

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[14] The future values of an NPD project change over time, due to factors specific to the project in reality. However, those factors are not generally related to the stock markets' previous reactions toward the project, therefore, the *ceteris paribus* assumption is valid here.

[15] The wealth effect of a product announcement is not exactly linearly proportional to the innovation announcement of the same NPD project. The exact value of the wealth effect is as follows:

$$\frac{FV}{(1+r_2)^{S_2}}-\frac{FV}{(1+r_1)^{S_1}}=FV\left[\frac{(1+r_1)^{S_1}-(1+r_2)^{S_2}}{(1+r_1)^{S_1}(1+r_2)^{S_2}}\right]=\frac{FV}{(1+r_1)^{S_1}}\left[\frac{(1+r_1)^{S_1}-(1+r_2)^{S_2}}{(1+r_2)^{S_2}}\right]$$

where r_1, r_2 are the discount rates for the innovation announcement and product announcement;

s_1, s_2 are the lenth of time between the realization of future values and the announceements;

FV is the future value of the NPD project;

$r_1 > r_2$ and $s_1 > s_2$

previously underestimated risks associated with a product launch. The previously underestimated risks may include market uncertainties and the large financial commitments to inventory deployment, production and supply chain management, and marketing activities. These risks are often not clear when product launch announcements are made, and are often underestimated (Calantone 1999; Guiltinan 1999; for an integrated review, please see chapter 3 of this dissertation). By definition, the size of the underestimation is usually positively proportional to the previous estimation, which in turn is negatively related to the size of previous wealth effective (i.e., the product announcement of the same NPD project). Consequently, since the underestimation of launch risks at product announcement stages offsets a large portion of the otherwise positive increase in NPV due to the reduced risks of the entire project, it can be argued that:

H2: The wealth effect of a new product project's product announcement has *a negative impact* on the wealth effect of that project's *launch announcement*.

Firms' Relative R&D Intensity

Organizations within an industry often differ in technological capability; that is, they differ in their R&D activity and spending relative to other firms in the same industry. Firms that continually outspend their rivals in R&D tend to initiate more innovation projects (Kelm et al.1995). As such, investors typically expect innovation announcements by firms with high R&D intensity relative to their industry rivals. Consequently, the market reaction toward innovation announcements by these firms will be smaller.

> **H3a: A firm's relative R&D intensity has *a negative impact* on the wealth effect of *an innovation announcement* made by that firm.**

However, the high R&D intensity firms not only innovate more, but they also have greater technological capability and thus enjoy the benefits of any economies of scale inherent in the NPD process (Burgelman and Maidique 1989). Therefore, the products that are successfully developed from these firms tend to have greater potentials. Therefore, product announcements made by these firms, which indicate the successfully completion of the product development stage of NPD projects, are rewarded with larger stock market reactions.

> **H3b: A firm's relative R&D intensity at the time of the project's launch announcement has *a positive impact* on the wealth effect of *a product announcement* made by that firm.**

Once a new product is developed, a firm's technological capacities are not very relevant to the product's commercialization process. Therefore,

> **H3c: A firm's relative R&D intensity has *no impact* on the wealth effect of *a launch announcement* made by that firm.**

Industry Concentration

Industry concentration is the degree to which product markets are dominated by a small number of firms, which, as many economists have argued, is that the benefits arising from R&D efforts must be positively associated with high market concentration. However, the empirical evidence has been mixed (cf. Kamien & Schwartz, 1982). Some evidence suggests that relationship holds true in the case of R&D expenditures (Doukas & Switzer, 1992), but other findings suggest that when R&D intensity is controlled, industry concentration does not matter (Chanet al., 1990). Kelm et al. (1995) argue that, for innovation announcements, industry concentration is not particularly useful for judging either the appropriateness of an innovation for an industry or the ability of a firm to undertake innovation. However, it is important when investors are assessing future cash flows when the product is already launched to the market. Therefore,

H4a: The concentration of a firm's industry has *no impact* on the wealth effect of an *innovation announcement* made by that firm.

H4b: The concentration of a firm's industry has *no impact* on the wealth effect of a *product announcement* made by that firm.

H4c: The concentration of a firm's industry has *a positive impact* on the wealth effect of a *launch announcement* made by that firm.

Firms' Growth Rates on Sales

A firm's growth rate is a proxy for both the firm's growth status and its marketing capability. Growth rate is not particularly useful for investors to assess an innovation announcement, as investors' primary concern is the focal firm's technical capabilities. When a product announcement is made, investors' primary concern is the market potentials of the product. When the sales growth rate is low, which implies sales plateau and product maturity, product extensions (Chaney et al., 1991) offer a way for firms to extend product life cycles and stimulate growth. Therefore, investors will give a higher value to a product announcement when the growth rate is low. However, when a product is launched, the investors' primary concern is the firm's marketing capability. Therefore, a high sales growth rate implies a greater marketing capability, which, in turn, leads to larger wealth effects.

H5a: A firm's growth rate has *no impact* on the wealth effect of *an innovation announcement* made by that firm.

H5b: A firm's growth rate has *a negative impact* on the wealth effect of *a product announcement* made by that firm.

H5c: A firm's growth rate has *a positive impact* on the wealth effect of *a launch announcement* made by that firm.

Firm Size

Small firms need product innovation to survive in the market, but large firms introduce new products only to stay on top of the market (Porter, 1980; and Chaney et al., 1991). Thus, innovation announcements should be more highly valued for small firms than for large firms. In addition, large firms' innovations might have less unanticipated information than those of small firms because information production and dissemination are positive functions of firm size (Atiase, 1985; Chaney et al., 1991; Kelm et al., 1995; and others). However, large firms have more marketing, engineering, financial, and production and operation capabilities and resources in turning developed products into commercial successes.

H6a: A firm's size has *a negative impact* on the wealth effect of *an innovation announcement* made by that firm.

H6b: A firm's size has *a positive impact* on the wealth effect of a *product announcement* made by that firm.

H6c: A firm's size has *a positive impact* on the wealth effect of *a launch announcement* made by that firm.

Free Cash Flow

Free cash flow is defined as cash flow remaining after all the positive net present value projects are funded at the relevant cost of capital (Jensen 1986). Jensen (1986) argues that managers endowed with free cash flow will invest wastefully, rather than pay out to shareholders. Investments in new product can be viewed as such use of free cash flow (Chen and Ho 1997; Chen et al. 2002). Therefore, the potential agency costs of new product investments can be higher for firms with high free cash flow.

On the other hand, new product investments by low-free-cash-flow firms increase the chance that the firm will seek new external financing, which often implies monitoring. The firm's willingness to undergo such monitoring can be a favorable signal (Szewczyk et al., 1996). Therefore, the free cash flow theory predicts that the market response to a new product announcement will be inversely related to the firm's level of free cash flow. However, the pecking order theory would seem to suggest the opposite relation. Therefore,

H7a: A firm's free cash flow has *a negative impact* on the wealth effect of *an innovation announcement* made by that firm.

H7b: A firm's free cash flow has *a negative impact* on the wealth effect of *a product announcement* made by that firm.

H7c: A firm's free cash flow has *a negative impact* on the wealth effect of *a launch announcement* made by that firm.

Debt Ratio

Jensen (1986) suggests that researchers can consider a firm's debt ratio as an alternative measure of free cash flow. According to Jensen's free cash flow theory, higher debt ratios imply firms' willingness to allow external monitoring in their investment decisions, which is favored by the stock market. Therefore, there is a positive relation between the market response to corporate announcements of investment decisions and the announcing firm's debt ratio. However, empirical studies (Chen and Ho 1997; Chen et al. 2002) failed to find a significant relation between wealth effects of NPD announcements and debt ratio.

H8a: A firm's debt ratio has *a positive impact* on the wealth effect of *an innovation announcement* made by that firm.

H8b: A firm's debt ratio has *a positive impact* on the wealth effect of *a product announcement* made by that firm.

H8c: A firm's debt ratio has *a positive im*pact on the wealth effect of *a launch announcement* made by that firm.

Investment Opportunities – Tobin's Q

The availability or lack of investment opportunities, which are often measured by Tobin's Q, can be an important consideration in assessing the value of corporate strategic investments (Lang, Stulz, and Walkling, 1989 and 1991; Szewczyk, Tsetsekos, and Zantout, 1996; and others). NPD investments that are signaled by an innovation announcement or a product announcement can be signals of a firm's intention to continue its investment in an NPD project. The stock market will react more favorably to the announcement if the investment opportunities are greater. In fact, Chen and Ho (1997) find a significantly positive relationship among a firm's announcement, Tobin's q, a proxy for the firm's investment opportunities, and the stock market's share-price response to an NPD announcement.

H9a: A firm's Tobin's Q has *a positive impact* on the wealth effect of *an innovation announcement* made by that firm.

H9b: A firm's Tobin's Q has *a positive impact* on the wealth effect of *a product announcement* made by that firm.

H9c: A firm's Tobin's Q has *no impact* on the wealth effect of *a launch announcement* made by that firm.

Methodological Basis for the Research Objectives and the Model

The Measurement of the Key Variables

The three types of NPD announcements are denoted by i, where i = 1 refers to an innovation announcement, i = 2 refers to a product announcement, and i = 3 refers to a launch announcement.

A firm's R&D intensity ($R\&D_i$) is defined as the intensity of the firm's R&D effort (R&D per dollar of net sales) divided by its industry's total sales for the fiscal year prior to the *i*th announcement (as in Chen et al. 2002; Kelm et al. 1995).

Industry concentration ($CONCN_i$) is defined as the ratio of the total sales for the four largest firms in the industry to total industry sales prior to the *i*th announcement, which is a common standard for evaluating marketing concentration (Doukas and Switzer 1992; Kelm et al. 1995).

Firm growth rate ($GROW_i$) is defined as a firm's sales growth prior to the *i*th announcement.

Firm size ($SIZE_i$), similar to Kelm et al. (1995), is defined as the logarithm of a firm's total sales for the fiscal year prior to the *i*th announcement.

Free cash flow ($CASH_i$) is defined as operating income before depreciation minus interest expense, taxes, preferred dividends, and common dividends, divided by book value of total assets, for the fiscal year prior to the *i*th announcement, which is consistent with past studies (e.g., 2002; 1995; Lang et al. 1991; Lehn and Poulsen 1989).

Debt ratio ($DEBT_i$) is the book value of total debt divided by the book value of total assets for the fiscal year prior to the *i*th announcement.

Tobin's Q ($TOBIN_i$) is used to estimate a firm's investment opportunity, which is defined as the ratio of the market value of a firm to the replacement cost of its assets. In this study, Tobin's q is calculated based on Chung and Pruitt's (1994) method, which approximates Tobin's Q as (MVE+PS+DEBT)/TA, where

MVE is the product of a firm's share price and the number of common stock shares outstanding, PS is the liquidating value of the firm's outstanding preferred stock, DEBT is the value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long-term debt, and TA is the book value of the total assets of the firm prior to the *i*th announcement. This measure is widely used and has been accepted in previous studies (Barclay and Smith 1995a; Barclay and Smith 1995b; Chen and Ho 1997; Chen et al. 2002; Denis 1994).

The wealth effect of an NPD announcement CAR_i, is the cumulated abnormal returns during the NPD announcement period (i.e., event window). CAR is calculated as the cumulated differences between the actual return and an expected return generated by the market model, of which the parameter is estimated using the ordinary-least-squares (OLS) method. The market model uses the value weighted Center for Research in Security Prices (CRSP) index as a proxy for market returns and the data over a period from 120 to 21 days before the announcement date. The significance tests are conducted using the *t*-statistic as well as the Wilcoxon z-statistic (for a detailed discussion, see Cowan 2003). The event window is a period from 1 to 0 days before the announcement date.

The Model

The proposed study on the wealth effects of announcement will use new product projects as the unit of analysis. Three sequential events will be studied for each project: innovation announcement, product announcement, launch announcement. For each new product project, the hypothesized relationships among the key variables can be described as by three equations:

$$\begin{aligned} CAR_1 = {} & \beta_{1,0} + \beta_{1,1} R\&D_1 + \beta_{1,2} CONCN_1 + \beta_{1,3} GROW_1 + \beta_{1,4} SIZE_1 \\ & + \beta_{1,5} DEBT_1 + \beta_{1,6} CASH_1 + \beta_{1,7} TOBIN_1 + \mu_1 \end{aligned} \tag{4.1}$$

$$\begin{aligned} CAR_2 = {} & \beta_{2,0} + \beta_{2,1} R\&D_2 + \beta_{2,2} CONCN_2 + \beta_{2,3} GROW_2 + \beta_{2,4} SIZE_2 \\ & + \beta_{2,5} DEBT_2 + \beta_{2,6} CASH_2 + \beta_{2,7} TOBIN_2 + \beta_{2,8} CAR_1 + \mu_2 \end{aligned} \tag{4.2}$$

$$\begin{aligned} CAR_3 = {} & \beta_{3,0} + \beta_{3,1} R\&D_3 + \beta_{3,2} CONCN_3 + \beta_{3,3} GROW_3 + \beta_{3,4} SIZE_3 \\ & + \beta_{3,5} DEBT_3 + \beta_{3,6} CASH_3 + \beta_{3,7} TOBIN_3 + \beta_{3,8} CAR_2 + \mu_3 \end{aligned} \tag{4.3}$$

Data Collection

In previous studies (Chaney and Devinney 1992; Chaney et al. 1991; Chen and Ho 1997; Chen et al. 2002; Eddy and Saunders 1980; Kelm et al. 1995; Pardue et al. 2000) on the wealth effects of NPD announcements, announcement data were acquired using a "kitchen sink" type of approach, in which any news entry in the Dow Jones News Index (and some other major news indexes) with some key words such as "new products," "product introduction," "launch," etc. is considered an NPD announcement. Thus there are several major shortcomings of this approach:

First, many non-NPD announcements are included in the collected data, so the result is a very great amount of "data noise." Second, the Dow Jones Index does not include all NPD announcements, but only those that are considered newsworthy to the general public, instead of to the investors' communities for particular firms. It also implies bias against industrial innovations and products.

Third, it is not necessary for the Dow Jones Index to report an NPD announcement on the date when the event occurs. Instead, the reporting dates can be many days and even months later than the actual date/s of the events/announcements. This circumstance further dilutes the accuracy of the collected announcement data.

Fourth, as an index, the Dow Jones Index does not contain the actual reports of NPD announcements, but on contains sets of keywords derived from the news reports. As such, news indexes such as Dow Jones do not provide enough information to classify NPD announcements into innovation announcements, product announcements, and launch announcement as required in this study.

Finally, because the Dow Jones Index only collects a small portion of NPD announcements, in most cases, the Dow does not collect all the announcements related to a particular NPD project over its entire life cycle. Therefore, it is usually impossible to use the Dow Jones Index to trace all three sequential announcements for an NPD project, even if the focal firm had made all the announcements.

In order to avoid the shortcomings of previous data collection methods and to enable the study to use new product projects instead of announcements as the unit of analysis, a data collection scheme was developed to first identify important NPD projects and then to trace these NPD projects' innovation announcements, product announcements, and launch announcements. The announcement data collection scheme is described as follows:

1. *Identify a list of representative firms to focus on the search for NPD projects.*

   Sinice there are about 20,000 to 30,000 new products launched annually in the U.S. consumer market alone, it is impossible to collect data on all NPD projects from every firm or every industry. Therefore, it is essential to collect a representative sample of NPD projects. This study focuses on a set of 134 US public firms that were identified by Standard & Poor's (2002) as the key players in the information technology sector, which has been one of the most active industry sectors in innovation and new product development activities for the last two decades.

2. *Identify the most important NPD projects for each identified firm.*

   For each identified firm, a search was initiated for NPD projects in LexisNexis' Business & Finance database and in the Industry News database[16] using the firm's name and different combinations of keywords such as "new product," "product development," "breakthrough," "next generation," "cutting edge," "innovation," "product introduction," "launch," etc. Due to data availability, most of the NPD projects have been selected from the ten-year period from 1994 to 2004. In addition, Standard & Poor's (2002) also provides a list of key product categories for each firm, which have also been used as keywords. However, the search results were reviewed and only a few

[16] LexisNexis' Business Finance database's data sources include 670 newspapers, magazines, journals, and wires & transcripts. Industry & Market database collects data from 1125 News sources from over 25 industries.

(i.e. one to three) of the most important projects have been selected for each firm. The importance of an NPD announcement is judged by the frequency of reports by different media sources on the NPD projects.

3. *Search for identified NPD projects' innovation announcements, product announcements, and product launch announcements.*

   For each identified NPD project, a search was initiated for all announcements and reports based on the name of the NPD project in LexisNexis' Business & Finance database and in the Industry News database for the chosen time period. Since firms often change NPD projects' names over the NPD projects' life cycles, special attention has been paid to the name changes of NPD projects, in order to trace the entire NPD life cycles of the NPD projects. From the results of the search, identification of the earliest type of announcement or report indicated the following: 1) the innovation activities for the NPD project was initiated, but the product had not been developed (i.e., an innovation announcement); 2) the earliest announcement or report indicated that a product or prototype from an NPD project had been developed or demonstrated, but had not been introduced to the market (i.e., a product announcement); and 3) the earliest announcement or report indicated that a product was being shipped, installed or launched to the marketplace (i.e., a launch announcement).

Based on the collected announcement data, the wealth effect for each announcement could be estimated using daily stock prices from the Center for

Research in Security Prices (CRSP) database[17]. Other key variables were calculated based on data from Compustat[18] and the announcement data. Finally, the wealth effects data and other key variable data were reconciled and merged based on the names of the selected NPD projects.

Sample Characteristics

Based on the Standard and Poor's (2002) list of 134 key firms in information technology, 516 NPD announcements on 207 NPD projects from 103 firms were identified. The remaining 31 firms were not applicable to the current study, due to the nature of their business (e.g., consulting, manufacturing contractor, service, etc.). A few of the 207 NPD projects were dropped due to lack of available data in the CRSP and Compustat databases. In addition, those NPD projects that did not have all the three sequential announcements are also dropped. The final sample size is 104 NPD projects from 56 firms. These NPD projects are from 18 industry categories [defined by the Standard Industrial Classification (SIC code)] in the information technology section. Table 4-2 shows the distribution of the sample NPD projects and their associated firms across industries.

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[17] The Center for Research in Security Prices (CRSP) maintains the most comprehensive collection of standard and derived security data available for the NYSE, AMEX and Nasdaq Stock Market. CRSP is a research center at the University of Chicago Graduate School of Business, and maintains historical data spanning from December 1925 to the present. CRSP's trademark of unique issue identifiers tracks a continuous history of securities, providing a seamless time-series examination of the issue's history. CRSP's unparalleled accuracy and dedication to excellence has made CRSP data a staple of academic and commercial research and data analysis throughout the world.

[18] Compustat is a database of financial, statistical, and marketing information. It provides more than 300 annual and 100 quarterly Income Statement, Balance Sheet, Statement of Cash Flows, and supplemental data items on more than 7500 publicly held companies

Table 4-2 Sample Classification by Industries

	Standard Industrial Classification (SIC)	Industry Name	Number of NPD Projects	Number of Firms
1	3559	SPECIAL INDUSTRY MACHY, NEC	3	2
2	3560	GENERAL INDUSTRIAL MACH & EQ	2	1
3	3570	COMPUTER & OFFICE EQUIPMENT	2	1
4	3571	ELECTRONIC COMPUTERS	10	3
5	3572	COMPUTER STORAGE DEVICES	4	4
6	3576	COMPUTER COMMUNICATION EQUIP	1	1
7	3577	COMPUTER PERIPHERAL EQ, NEC	2	1
8	3578	CALCULATE,ACCT MACH,EX COMP	1	1
9	3661	TELE & TELEGRAPH APPARATUS	5	4
10	3663	RADIO,TV BROADCAST, COMM EQ	7	3
11	3669	COMMUNICATIONS EQUIP, NEC	1	1
12	3674	SEMICONDUCTOR,RELAT ED DEVICE	26	10
13	3695	MAGNETC,OPTIC RECORDNG MEDIA	2	1
14	3826	LAB ANALYTICAL INSTRUMENTS	2	2
15	7370	CMP PROGRAMMING,DATA PROCESS	6	3
16	7372	PREPACKAGED SOFTWARE	27	17
17	7373	CMP INTEGRATED SYS DESIGN	2	2
18	7374	CMP PROCESSING,DATA PREP SVC	1	1

Even though a few NPD projects are dated as early as 1982., most of the sample NPD projects are dated from 1994 and 2004, due to the limits of LexisNexis' Business & Finance database and the Industry News database The innovation announcements for the sample NPD projects are dated from 1982-2004, the product announcements are dated from 1983-2004, and the launch announcements are dated from 1984-2004. The NPD projects in the sample include not only many well-known products such as Apple's ipod, Intel's Pentium 4, Microsoft's Xbox, etc., but also many lesser-know industrial products such as Thermo Electron's EGIS(R) portable explosives detector, Ultratech's Saturn Spectrum 3 (semiconductor manufacturing equipment), and Tripos' ChemSpace Technology (database library for drug discovery).

Data Analysis and Results

Data Analysis

The three-equation model (i.e., equation, 4.1, 4.2 and 4.3) were tested using a three-stage least squares (3SLS) regression analysis (Judge et al. 1985), a procedure for estimating parameters in linear models by least squares. The 3SLS procedure is often used in estimating parameters in systems of several equations in marketing literature (e.g.,Calantone and di Benedetto 1988b; Han et al. 1998; Song et al. 1997). When the equations in a system are interdependent such that the dependent variables from one equation appear as independent variables in other equations, then ordinary least squares (OLS) estimates can be inconsistent. That is, if the equations are statistically estimated one at a time, serious biases may result from using variables in more than one equation

(Calantone and di Benedetto 1988b; Gujarati 2003). The 3SLS estimation approach provides consistent and efficient parameter estimates of models incorporating reciprocal causation and interdependent error terms (Gujarati 2003).

The Results

The 3SLS estimation results for the three simultaneous equations are reported in table 4-3, 4-4 and 4-5. The system weighted R square for 3SLS models is 0.1718, which is relatively large in this type of study (e.g., Chen et al. 2002; Kelm et al. 1995) and indicates the good fit of the model. In addition, the parameter estimates from the 2SLS estimations are largely consistent with the 3SLS results, which show that results are robust[19].

The results show that the wealth effects of innovation announcements' impacts on the wealth effects of product announcements are positive and statistically significant ($p < 0.05$). Meanwhile, the wealth effects of the product announcements' impacts on the wealth effects of the launch announcements are negative as hypothesized, but statistically non-significant. Therefore, H1 is supported by the results, while H2 is not supported. The non-significant result for H2 might be due to the small sample size that has limited the statistical power of the test.

The results show that the impact of the firms' relative R&D intensity on both the wealth effects of innovation announcements and the wealth effects of

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[19] To further test the robustness of the results, the three-equation model is tested based on wealth effects estimated based on other event windows (i.e., -1 to +1; -1 to +5), and a different benchmark (i.e., the comparison period mean-adjusted return model) was used to estimated the wealth effects of NPD announcements. The 3SLS results are similar to the results presented here.

product announcements are not significant, and thus H3a and H3b are not supported. Meanwhile, as predicted by H3c, R&D intensity's impact on the wealth effects of launch announcements was not significant. Thus H3c is supported.

For industry concentration, the results show that R&D intensity's impact does not significantly impact either the wealth effects of innovation announcements or product announcements, which are consistent with H4a and H4b. In addition, the coefficient ($P>0.10$) for the relationship between industry concentration and the wealth effects for launch announcement is statistically not significant and thus fails to support H4c.

For sales growth rate, the results show that the growth rate's impact on innovation announcements' wealth effects is not significant, which is consistent with H5a. However, its impact on the wealth effects of product announcements is also not significant, which indicates that H5b is not supported. In addition, H5c is supported, as the coefficient of growth rate in equation 4.3 is positive and significant ($P>0.10$), as predicted by H5c.

For firm size, it's coefficient in equation 4.1 is negative and significant ($P<0.05$) as suggested by H6a. Meanwhile, its coefficients in both equation 4.2 and 4.3 are positive and significant ($P<0.10$ and $P<0.05$ respectively) as hypothesized by H6b and H6c. Therefore H6a, H6b, and H6c are all supported.

For debt ratio, the coefficients in equation 4.2 and 4.3 are positive as predicted by H8b and H8c, but are not significant. Even though the two hypotheses are not supported by the results, this outcome is hardly a surprise. In fact, the results are consistent with previous empirical findings (Chen and Ho

1997; Chen et al. 2002) in this area. In addition, the debt ration's impact on the innovation announcements' wealth effects is also insignificant, even though it is negative as hypothesized by H8a. The non-significant effects of debt ratio might be due to the small sample size which leads to low statistically power in the test.

For free cash flow, coefficients in equation 4.1, 4.2, and 4.3 are all negative as predicted by the H7a, H7b and H7c. However, only the coefficients for equation 4.2 is statistically significant ($P<0.05$ respectively). Therefore, H7b is supported, while H7a and H7c are not supported by the results. This might be because that agency costs are the highest at the new product development stage. Therefore, a low cash flow at this stage is a critical indicator that fund are not wasted on a NPD project.

For Tobin's Q (i.e. the proxy for investment opportunities), its coefficient in equation 4.2 is positive and significant ($P<0.05$), and thus supports H9b. Its coefficient in equation 4.3 is not significant, which is predicted by H9c. However, H9a is not supported, as the coefficient in equation 4.1 is not significant at any level. This might be due to the fact that an innovation announcement indicates potential investment in the future, while Tobin's Q only reflects the present investment opportunities, which are thus not very useful for investors to value the NPD project's potential value in the future.

Table 4-3 Parameter Estimates for Equation (4.1)

	$R\&D_1$	$CONCN_1$	$GROW_1$	$SIZE_1$	DEBT	$CASH_1$	$TOBIN_1$
CAR_1	0.0698	-0.0020	-0.0200	-0.0060**	-0.0385	-0.0051	0.0003

Table 4-4 Parameter Estimates for Equation (4.2)

	$R\&D_2$	$CONCN_2$	$GROW_2$	$SIZE_2$	$DEBT_2$	$CASH_2$	$TOBIN_2$	CAR_1
CAR_2	0.0122	-0.0077	0.0139	0.0051*	0.0139	-0.1311**	0.0021**	0.6979**

Table 4-5 Parameter Estimates for Equation (4.3)

	$R\&D_3$	$CONCN_3$	$GROW_3$	$SIZE_3$	$DEBT_3$	$CASH_3$	$TOBIN_3$	CAR_2
CAR_3	0.0831	-0.0089	0.0359*	0.0054**	0.0211	-0.2263	-0.0016	-0.0725

* $p < 0.10$
** $p < 0.05$

Discussion

Theoretical Contributions

In this study, the wealth effects of New Product Development (NPD) announcements through the entire life cycle of NPD projects are investigated. It is the first of study of its kind that has traced NPD projects and their announcements over their entire project life cycles. As a result, the study is able to investigate how a previous announcement affects the wealth effect of a subsequent announcement from an NPD project. That is, this study does not focus on the wealth effects of an event per se (i.e., an announcement, or a product launch), but on the relationships among a set of wealth effects due to the sequential events for as NPD project, from the innovation announcement, to the product announcement, to the launch announcement. The unit of analysis is not NPD announcements, but NPD projects.

The study has demonstrated that the size of an NPD announcement's wealth effect is not only affected by the technology and market (both firm and industry) variables at the time of the announcement, but also by the carryover of wealth effects from the previous announcement of the same NPD project. The results shows that an NPD project's innovation announcement's wealth effect has a positive link to its subsequent announcement's (i.e., product announcement) wealth effect, which, however, has no impact or a negative impact on the wealth effects of the launch announcement of the same project. This finding is consistent with our predictions based on previous new product literature on how risks evolve over the life cycles of NPD projects, even though little work has been done studying the area of NPD announcements.

The study also demonstrates that the relationship of technology and market (firm and industry) variables to the wealth effects of announcements at different stages of NPD projects is very different in the following ways: 1) for the wealth effects of innovation announcements, firm size (negative) are the most important factors; 2) for the wealth effects of product announcement, firm size (positive), free cash flow (negative), firm's investment opportunities (positive), and the wealth effects of innovation announcements from the same NPD projects (positive) are the most important factors; 3) for launch announcements, sales growth rate (positive), firm size (positive), and the wealth effects of product announcements from the same NPD projects (negative) are the most important factors.

The differences in the factors' importance and the directions of the factors' impacts on the wealth effects are due to how investors assess NPD projects' risks at different stages of NPD projects. In general, at the innovation stage, investors are more concerned with the announcing firms' ability to finance the NPD projects, their technological capabilities, and the relative importance of the projects to the firms. At the commercialization stage (i.e., product announcements), investors are more concerned with the firms' technological capabilities, investment opportunities, market conditions, marketing capabilities, and agent costs. At new product launches, investors are more concerned with firms' market conditions, marketing capabilities, and agent costs.

Methodological Contributions

From a methodological standpoint, this study is the first research known to this author that links a series of subsequent events to a single project and examines the dynamic effects of a project's announcements. This approach provides several advantages over the cross section regression approach employed in previous event studies:

First, it enables researchers to investigate the dynamics of related events over a project's life cycle, instead of considering an isolated event, which often fails to fully capture a firm's strategic intentions on the focal project;

Second, it helps researchers to reconcile the differences between the long-term effects event study that is predominantly used in strategic management literature and the short-term effects event study that is predominantly used in finance and accounting literature ((Lubatkin and Shrieves 1986);

Third, it offers a new way to identify events and collect event data, which not only avoids the data noises and errors from the existing event data collection methods, but also captures the actual content of the events (i.e., actual announcements) and much more accurate event dates;

Finally, it enables the researchers not only to examine the effects of firm-related and industrial-related variables on the events' wealth effects, but also to consider the effects of the characteristics of the events themselves (i.e., the stages of NPD announcements in the current study).

Managerial Contributions

From a managerial standpoint, this study offers several strategic insights regarding how a firm's top management can manage the stock market's reactions toward various types of NPD announcements:

First, it is more rewarding for firms of smaller size, lower research spending, and higher debt ratios to make innovation announcements because such firms are less expected by investors to have innovation capabilities;

Second, it is more rewarding for firms with large research spending, firm size, lower cash flows, and higher investment opportunities to make product announcements because firms with such characteristics are more likely to successfully and efficiently proceed to the new products launch stage;

Third, it is more rewarding for firms with higher market growth rates, lower cash flows, and lower industry concentrations to make product launch announcements because investors tend to consider firms with such characteristics to be more successful and efficient with their product launches;

Fourth, the wealth effect of an innovation announcement has an augmenting effect on that of the subsequent product announcements. Therefore, a successful innovation announcement is not only rewarded with a strong positive stock market reaction, but also is further rewarded by augmented reaction toward its subsequent new product effects. Therefore, to fully capture a PD project's wealth effects, it is critical to ensure a successful innovation announcement.

Fifth, there is a tradeoff between the wealth effects of product announcements and launch announcements. That is, an increase in the wealth effect of a product announcement often leads to a reduced wealth effect of its subsequent launch announcement. Thus, it is rather futile for firms to achieve large wealth effects for both the product announcement and the launch announcement of the same NPD project. Therefore, with an NPD project, a firm should focus its resources on only one of the two announcements, instead of on both;

Finally, firms need to take a holistic view of NPD announcement decisions on new projects, as NPD announcements not only result in immediate stock market reactions, but they also affect the stock market's reactions toward the firm's subsequent announcements. For example, a firm with a high growth rate might choose not to hype/promote its product announcement. Instead the firm might focus on its efforts on the launch announcement since the reduced wealth effects (due to high growth rate and less promotion effort) on the product announcement will lead to an increase in the wealth effect of the launch announcement, which is also a benefit from the high growth rate at the launch stage.

In sum, it is important for managers to understand that the effects of the product announcements not only depend on the content of the current announcement and the status of the NPD project, but also on the effects of previous announcements as well as on the current market and firm conditions. Managers can use this knowledge to fine tune NPD announcements and thus manage investors' reactions toward an NPD project over the project's life cycles. Potentially, understanding the effects of product announcements could allow managers to maximize an NPD project's wealth effects over its entire life cycle, knowledge which could be used to hedge against future failures of an NPD project.

Future Research

The current study illuminates several directions for future research to extend the current study:

First, a more elaborated model should be developed to accommodate not only those NPD projects that had made all three types of announcements, but those projects that had only made one or two types of announcement during their life cycles. It would make the findings generalizable to a much larger set of scenarios in NPD announcements. It would also allow the use of the entire data set collected for this study, which would leads to greater statistical power in the test of the hypotheses.

Second, a more thorough content study on the collected NPD announcement data could be conducted. The NPD announcements could then be coded into several content related variables (for example, the innovativeness of an NPD project). Doing so would provide further information on how NPD announcements can be devised to maximize their wealth effects.

Third, NPD data on other industries should be collected, which not only would enable a more robust test of theories presented in this current study, but could also investigate the differences on NPD announcements across industries.

Fourth, NPD data on a larger time horizon should be collected, as the current study is limited to NPD projects over the last 10 years, a fact which might introduce bias due to the huge technology bubble and its burst during late '90s and the beginning of the 21st century.

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