Market Uncertainty and Dynamic New Product Launch Strategies: An Systems Dynamics Model

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ABSTRACT

New products are intrinsically associated with high level of market uncertainty, and product launches often fail because launch strategies formulated based upon pre-launch forecasts cannot accurately capture actual market conditions. While research generally recognizes the importance of flexibility in new product launch, it has rarely examined the dynamic adjustments after initial launch, largely due to the limitation of conventional methodologies in modeling over time feedbacks and interactions. This study develops a system dynamics model of new product launch that formalizes the adjustments of launch scale according to actual market conditions and the dynamic interactions among launch scale and various tactical elements of product launch including advertising, distribution, pricing, manufacturing and inventory management.

This study makes a first attempt to bring systems dynamic modeling to new product launch research and illustrates a new approach to examining dynamic feedbacks in the new product launch process. The model developed in this study illustrates why and how dynamic approaches outperform static ones, and reveals important insights of the behavior of dynamic product launch strategies. The model can be used as a “flight simulator” in managerial training to help new product managers understand the dynamic interactions among different elements of new product launch.

Key words: New product launch, market uncertainty, system dynamics model

MANAGERIAL RELEVANCE STATEMENT

This study provides insights on managing market uncertainty for new product launches. The model illustrates how launch scale and tactics can be adjusted in response to actual market demand after initial launch, and suggests such adjustments require building in flexibility in pre-launch planning and developing explicit procedures and tools of assessing actual market conditions. The system dynamics model developed in this study can be used as a “flight simulator” in managerial training to help new product managers understand the dynamic interactions among different elements in new product launch, especially during the adjustment of launch scale in response to new market information after initial launch.

I. INTRODUCTION

Product launch is often the most crucial stage in the new product process. Empirical studies have consistently shown that proficient product launch greatly improves the chances of new product success and even a superior product could fail due to poor launch strategies [1], [2], [3]. Product launch also involves the largest investment in the entire new product process. The production and marketing expenditures incurred at launch stage often exceed the combined expenditures of all previous development activities [2], [4], [5]. This large investment makes successful product launch even more critical for the firm.

New product launch is highly risky because new products - either new to the market or to the firm or both - are intrinsically associated with high level of market uncertainty [6] – [11]. Forecasts based upon historical market data and/or past experience often cannot accurately capture actual market conditions that are only revealed after initial launch [7], [12]. Yet launch strategies need to be formulated from forecasts and resource commitment needs to be made prior to launch. Firms are exposed to great risk when discrepancies occur between forecasts and actual market conditions.

Firms can use either: (1) a "fat" launch strategy, which involves large scale of resource commitment and dictates a large target market, large inventory deployment and large manufacturing capacity; or (2) a "narrow" launch strategy, which involves small scale of resource commitment and calls for niche marketing featuring small inventory deployment and manufacturing capacity. However due to market uncertainty, the scale of product launch could be either too large or too small compared to actual market demand. If the forecast is accurate, then the chosen launch strategy matches actual market conditions and the product launch is successful. If the forecast is inaccurate, a fat launch leads to oversupply with excessive inventory and manufacturing capacity resulting in financial losses; a narrow launch leads to short supply resulting in loss of market share and other opportunity costs (Table 1). Therefore product launch strategies formulated prior to launch are likely to be ineffective under actual market conditions. In fact, market uncertainty at product launch stage is one of the primary reasons for product launch failures [7], [13].

Insert Table 1 here

To solve this dilemma and better manage market uncertainty, launch strategies need to be adjusted according to actual market conditions after a new product is first launched. Existing research generally recognizes the importance of flexibility in new product launch, such as the importance of timing of promotion activities for product takeoff [10], and flexibility in manufacturing [14] and logistics [15] that may facilitate product launch. However, rarely has research systematically examined how launch strategies and tactics are dynamically adjusted according to feedbacks from actual market conditions after initial launch. With a rare exception [7], research on new product launch focuses on pre-launch forecasting [11], [12], [16] or formation of launch strategies and their contribution to product success without considering the time element or changes occurring after initial launch [17]-[26]. Given that substantial market information is only revealed after initial launch [7], it is crucial to examine how such information is utilized through adjustment of launch strategies and tactics, especially when market uncertainty is high.

Further, adjustments of launch strategies involve not only marketing variables such as pricing, advertising and channel development, but also supply chain elements such as manufacturing and inventory, which have been relatively neglected in the literature [15], [17], [27]-[29]. More importantly, marketing and supply chain aspects interact with each other during the launch process [27]-[30]. Poor inventory management and inefficient manufacturing may create supply constraints, and failing to adjust the supply chain may prevent or slow down the dynamic adjustments needed in new product launch. Increased production scale is also able to reduce unit cost of the product and allow the company to pursue more aggressive pricing. The study of dynamic launch strategies thus requires a consideration of both marketing and supply chain aspects and their dynamic interactions in the launch process.

One of the reasons that dynamic launch strategies have not been sufficiently examined in the literature is that the dynamic process involving feedbacks from market demand and interactions among various marketing and supply chain elements can not be modeled effectively with conventional methodologies that often take piecemeal, static, and linear modeling approaches. System dynamics modeling is a simulation method that is suitable for modeling complex systems involving interactions and feedbacks [31]. This approach therefore enables the examination of dynamic product launch strategies under market uncertainty.

This study employs system dynamics modeling to develop a dynamic model of new product launch that allows strategic adjustments during the launch process in response to actual market demand. The model formalizes the mechanisms through which overall launch scale is adjusted in response to product sales, and integrates both marketing and supply chain aspects to model the dynamic interactions among pricing, advertising, channel development, manufacturing and inventory management. In doing so, this study makes a first attempt to bring systems dynamic modeling to new product launch research, and the model provides a platform that can be easily extended to investigate complex interactions of various factors impacting new product launch. Further, by formalizing the feedback dynamics in new product launch, this study illustrates why and how dynamic approaches outperform static ones, revealing important insights of the behavior of dynamic launch strategies. The model can also be used as a “flight simulator” in managerial training to help new product managers understand the dynamic interactions among different elements of new product launch.

II. THE CONCEPTUAL FRAMEWORK

A. Market Uncertainty and Strategic Flexibility

The strategy literature has long recognized the importance of uncertainty and strategic flexibility. Strategy theories classify strategies into two types: intended strategies that formulate plans through assessing markets and developing budgeted programs [32], and emergent strategies that rely on ideas that surface from an organization’s interactions with its customers and markets. 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 [33]. This suggests that under market uncertainty, instead of planning for a particular future market scenario, firms should plan necessary flexibilities that allow for spontaneous response to the changing environment [34], [35].

The rationale of strategic flexibility has been applied in specific management domains such as marketing, logistics and operations management. The marketing literature has always recognized demand uncertainty and researched how to understand and meet changing customer needs [7], [36], [37]. The operations management literature has recognized manufacturing flexibility as an important dimension of firm competitive strategy and found flexible manufacturing to improve firm performance especially under high levels of uncertainty [14], [38]. Response-based logistics and supply chain management are found to provide flexibility that enables better management of inventory levels and more rapid reaction to market demand than anticipatory strategies based up demand forecasts [15], [39].

In the new product literature, the effects of uncertainty on various product development activities have been widely studied [6], [8], [9], [40], and management flexibility during the development process has been investigated with a real option approach [41]-[44]. When market uncertainty is high, flexible development plans that allow adjustments of decisions during the new product development process are found to increase overall project value and improve product success [41], [44].

However, new product studies have rarely considered market uncertainty and change at the launch stage. With rare exceptions [7], research focuses on pre-launch forecasting [11], [12], [16] or formulation of launch strategies without considering changes that may occur after initial launch [17]-[26]. Information on actual market demand is only revealed after a new product is first launched, and such information is extremely valuable for successful product launch, especially when market uncertainty is high [7]. Thus, product launch studies need to examine how new information revealed after initial launch is utilized and the dynamics of launch strategy adjustment based upon such information.

B. The Integration of Marketing and Supply Chain

New product development process has been recognized as an interdisciplinary process involving marketing, R&D and manufacturing, and new product success has been found strongly related to the amount of communication and cooperation among different functional areas [45] –[48]. Yet the coordination among marketing and supply chain during product launch has not received much attention. The majority of new product launch literature has overlooked supply chain activities such as inventory management, transportation and manufacturing [15], [17], [27]-[29].

Supply chain activities play important roles in product launch by converting market demand generated by marketing activities into actual product sales. Poor inventory management and inefficient manufacturing may create supply constraints and fail to realize sales [30]. Manufacturing and inventory management also involve costs that are significant parts of a firm's resource commitment to the launch and need to be considered in the overall launch strategy. For example, increased production scale reduces the unit cost of manufacturing and marketing a product, thus allowing the company to pursue more aggressive pricing. Thus, research on launch strategies needs to take a systematic view of the entire supply chain considering both marketing and supply chain activities and their interactions. An integrated approach that incorporates both marketing and supply chain aspects is especially necessary for dynamic launch strategies as the adjustment of launch strategies requires coordination among marketing activities and supply chain management activities [16]. While advertising and pricing can be adjusted to generate market demand, effective flow and storage of products facilitate rapid response to market demand by location and intensity.

C. A Dynamic Model of New Product Launch

Consistent with the literature, we look at product launch at two levels: strategic level and tactical level [15], [17], [21]. At the strategic level, we focus on one key dimension of product launch – product launch scale, defined as the resource commitment a firm makes to the launch [49]. It has long been noted that resource commitment in launching activities plays an important role in determining the speed of technology diffusion and product success [1], [49]. Tactical decisions involve the level and allocation of efforts related to marketing mix variables including advertising, pricing, channel management, manufacturing and inventory management [15], [21]. These tactical elements are determined by the overall launch scale, and in turn influence product sales [49]. For example, a large launch scale implies a mass marketing strategy that involves heavy advertising and promotion, high channel intensity, high production volume and low price. On the other hand, a small launch scale is often based on a niche marketing strategy featuring light advertising and promotion, low channel intensity, low production volume and high price. Large scale launch involves low price and lower profit margin but relies on high volume to generate profit, while small scale launch generate smaller sales volume but benefits from a higher profit margin.

Product launch adjustments can be made at both the tactical level and the strategic level. At the tactical level, firms can make short-term adjustments within the established launch strategy, i.e., keeping launch scale stable and adjusting specific tactics such as manufacturing or pricing. For example, production scale and inventory level is adjusted to match product sales; and as sales and production scale increase, price is adjusted down due to the reduction in unit costs. These adjustments reflect natural coordination among tactical launch activities. They enable adaptation to short-term and small changes in market demand and improve launch efficiency. However, when the discrepancy between forecasts and actual marked demand is high, the effectiveness of short-term tactical adjustments is limited as they are restricted with the same launch scale. To better respond to changes in market demand, firms need to make long-term adjustments at the strategic level, i.e., to adjust the launch scale, which in turn alters the existing tactical launch policies and consequently product sales. Figure 1 describes the relationships among launch scale, its tactical elements and product sales, and the dynamic feedbacks from product sales to launch strategy and tactics.

Based on this conceptual framework, we classify two types of launch strategies. (1) *Static launch strategies* that involve only short-term tactical adjustments without changes in the pre-determined launch scale. Within the same launch scale, tactical adjustments reflect natural interactions among the marketing mix variables. Even though involving changes, they are not dynamic at the strategic level. (2) *Dynamic launch strategies* that involve both short-term and long-term adjustments, where the initial launch scale is set before launch but dynamically adjusted during the launch process according to actual performance. We examine the behavior and performance of dynamic and static launch strategies under different market conditions.

Insert Figure 1 here

III. METHODOLOGY

A. System Dynamics Modeling

System dynamics modeling is a simulation method that models complex systems involving interactions and feedbacks [31]. It provides a way to examine the proposed framework that is a dynamic, complex system with interactions of variables over time. System dynamic modeling has been used in some studies evaluating new product development process and organizational decision-making [41], [50] – [55] and found to be a unique and useful tool for studying dynamic organizational phenomena [56], [57].

In system dynamics models, interactions are modeled with interconnected feedback loops representing paths from decisions to actions and then back to modified decisions [31]. Such loops are modeled in structures consisting stocks and flows. A "stock" variable reflects the state or accumulations of the system at any time point. A "flow" variable represents the activity that changes the value of the stock variable. The stock is the accumulation of the flow and the accumulation process is equivalent to integration in calculus.

Decisions are modeled as concrete applications of policies or decision rules [58], which are reflected in the equations that specify the interrelationships among variables. Formulation of decision rules (equations between variables) are based upon the understanding of the behavioral decision-making involved in the processes being modeled, either knowledge gained in existing literature or observation of the phenomenon. System dynamics philosophy rests on a belief that the behavior of system is principally determined by its structure [31]. As important as the specification of decision rules is, the dynamics of a system rely upon the structure of model more than the specific parameters.

In this study, we develop the model based upon previous modeling effort and empirical evidence on new product diffusion, advertising, manufacturing and inventory management. Due to the sparseness of system dynamic models on new product launch, existing model formulations are not available, and hence we rely on existing marketing and supply chain management theories and practices as a basis for formulating relationships in the model. This is consistent with practices in system dynamic modeling that suggest for areas of inquiry where there is little literature to build on, theories, practices and logic can be used to build the model [31], [57]. In presenting the model, we explain the decision rules that determine the values of key variables. The feedback interactions and overall dynamics of the model are reflected in the model structure consisting of these variables.

B. Research Design

To examine the behavior and performance of different launch strategies, we further classify static launch strategies into two categories: (1) fat launch strategies that involve large scale of resource commitment; and (2) narrow launch strategies that involve small scale of resource commitment.

To model different market conditions, we examine a key variable – market responsiveness, i.e., the extent to which market demand responds to launch efforts such as advertising and promotion. High market responsiveness implies the market responds effectively to marketing efforts, resulting in higher internal effects and external effects of the new product diffusion process, which lead to earlier demand takeoff [12], [59], [60]. Market responsiveness is an exogenous variable reflecting the nature of the product and the market that are independent of customers' goodwill and thus also not dependent on advertising.

Highly responsive market calls for large scale launch with abundant promotion and advertising efforts, while small scale launch with limited costs will be suited for less responsive markets. For a product that is either new to the market or to the firm or both (i.e. high market uncertainty), market responsiveness is unknown prior to product launch [12]. Based on speculations, the firm determines its launch strategies, which may turn out to effective or not, depending on actual market responsiveness. Thus, wrong speculations of market responsiveness are indication of high market uncertainty. To examine the behavior and effectiveness of different launch strategies, we examine the performance of fat, narrow and dynamic launch strategies under two scenarios: high market responsiveness and low market responsiveness (Table 2).

Insert Table 2 here

IV. THE MODEL

We first develop a base model of static launch strategies that only involve short-term adjustments. Simulation results of this model serve the purpose of validating the model and are also used to examine the behavior and effectiveness of static launch strategies. A dynamic model involving long-term adjustments of launch scale is then derived by modifying the base model, and is used to examine dynamic launch strategies.

A. Central assumptions

Several assumptions are used in developing the model. First, a cost-based penetration pricing strategy is adopted, i.e., firms aim at boosting market demand and penetrating the market quickly with low price. While various pricing strategies (such as skimming pricing) can be used in new product launch, the choice of penetration pricing is common and consistent with previous modeling effort in the new product literature [61]. Such pricing strategy benefits from large sales volume, and has been found to help firms achieve quick growth, reduce market penetration time and improve new product launch performance [62]-[64]. Further, the model assumes that distribution and manufacturing systems can be adjusted according to launch scale [14], [15], [49]. Although adjustment of production capacity may be more costly and time consuming than that of inventory or distribution outlets, it is possible to make such adjustments [14]. This is especially true considering the increasingly popular use of outsourcing as a flexible means of acquiring new production capacity [49], [65]. When building or purchasing new production capacity is too expensive or slow, production facilities can be rented or the manufacturing tasks can be contracted to others, and such contracts can be terminated when the capacity is no longer needed. Delays in the adjustment process are considered in the model. Thirdly, it is assumed prior to the new product launch managers are able to use their marketing knowledge and previous experience to plan resource investments and form general launch objectives, such as targets for advertising and distribution, budget for marketing and manufacturing spending and the corresponding sales expected from such spending [5] (P.531-536), [22]. Although the new product launch process is highly uncertain, such planning is necessary. In fact, setting launch objectives is the initial activity of the launch process [22], [66], [67], and poor planning and ill-defined objectives are found to lead to unsuccessful launches [22], [67]. In static launch strategies these goals stay unchanged, while in dynamic launch strategies they can be adjusted through launch scale according to the changing market demand. Lastly, the current model does not consider competition from other firms. Given the complexity of the model, in this research we focus on the dynamic interactions among different launch elements within a firm and look at how through such interactions a firm may adjust to changing market demand. Future research could extend this model to incorporate competitor actions and provide more insights on the dynamic interactions during new product launch.

B. The Base Model

Figure 2 presents the stock and flow diagram of the base model, which consists of 7 modules: product diffusion and demand management, advertising management, channel management, manufacturing and inventory management, pricing management, launch scale management, and the accounting module (not shown in Figure 2). Below we discuss the formulation of key equations in the model.

Insert Figure 2 here
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1) Product Diffusion and Demand Management Module: This module models the product diffusion process and the impact of firm actions in the process. This module is developed based upon the Bass model [59], [60]. The demand for a new product is the sum of demand from innovators, determined by external effect (such as mass media), and demand from imitators, determined by internal effect (i.e., interpersonal communications) [59], [60], [68], [69]. This approach is also used by Milling [61] in his model of innovation processes using a system dynamics approach. Without a consideration of the effects of advertising and pricing, the market demand at time t is:

$$D(t) = PC(t) * p + PC(t) * \frac{S(t)}{S(t) + PC(t)} * q \tag{1}$$

Where $PC(t)$ is the number of potential customers that are yet to adopt the product, $S(t)$ are the accumulated sales at time t, p is the coefficient of external effect, q is the coefficient of internal effect. Thus, $PC(t) * p$ is the number of innovators adopting the product, and

$PC(t) * \frac{S(t)}{S(t) + PC(t)} * q$ is the number of imitators adopting the product. We assume one customer only purchases one product [59], [60], [70], thus product sales are represented in product units instead of revenue.

Both external effect and internal effect are positively influenced by customers' goodwill $GW(t)$, which is influenced by advertising efforts (see the advertising management module), and market responsiveness MR, an exogenous variable with values between 0 and 1 representing the extent to which market demand respond to marketing efforts [59] [60] [70]. Thus:

$$D(t) = PC(t) * p * GW(t) * MR + PC(t) * \frac{S(t)}{S(t) + PC(t)} * q * GW(t) * MR \qquad (2)$$

The effect of price on demand is then incorporated according to generalized Bass model [61]. Following the economics literature we model the effect of price with the natural logarithm formulation of demand elasticity, which has been found to have numerous advantages over the simple percentage change formulation [71]. Specifically:

$$Q_j = Q_i e^{d*\ln\frac{Pj}{Pi}} \qquad (d < 0) \qquad (3)$$

Where Qi and Qj are the corresponding demand for prices P_i and P_j, and d is the coefficient of demand elasticity.

In the context of new product development, we define a reference demand (*RD*) as the total market potential, i.e., the total number of customers that may purchase the product [59] [60] [70]. The number of potential customers, which is equal to the gap between reference demand *RD* and actual accumulated sales $S(t)$, represents potential demand at time t, and it is influenced by price through the following equation:

$$PC(t) = Max((RD - S(t)) * e^{d*\ln\frac{P(t)}{RP}}, 0) \qquad (4)$$

Where *RD* is the reference demand, $S(t)$ is cumulative sales at time t, d is the coefficient of demand elasticity, $P(t)$ is the market price at time t, and *RP* is a reference price estimated by the managers based upon the cost of the product. When market price is equal to the reference price, the number of potential customers is equal to the difference between reference demand and cumulative sales. A maximization function is used to ensure the number of potential customers is above zero.

Lastly, demand for a product is converted to adoption only when it is covered by the distribution channel and fulfilled by retailers' inventory [30]. We use a variable e*ffective demand* to represent the demand that is covered by the distribution channel. The portion of effective demand that is met by the retailers' inventory determines the number of adopters (i.e. adoption rate), which accumulates to total sales. Thus adoption rate at time t is:

$$ADOP(t) = Min(ED(t), RINV(t)) \quad (5)$$

$$ED(t) = D(t) * CHN(t) \quad (6)$$

Where *D(t)* is demand, *ED(t)* is effective demand, *CHN(t)* is channel coverage, *RINV(t)* is the retailers' inventory. Channel coverage is calculated from the total number of channel outlets (see the channel management module) with an S-shaped function based on empirical evidence shown in Kotler and Lilien [72].

2) Advertising Management Module: Advertising is an important driver of new product sales and advertising spending is a key decision in new product launch [73]-[76]. This module models how advertising efforts affect the customers' goodwill toward a new product. The concept of customer goodwill has been widely used in the marketing and advertising literature to represent customers' positive feelings toward a product and their willingness to purchase the product [77], [78]. In this study, we model customers' goodwill as a stock variable ranging between 0 and 1. Consistent with previous modeling effort [76] [78], the stock of customers' goodwill is assumed to deteriorate over time at a constant attrition rate if no advertising effort is made to maintain it. Meanwhile, the stock of customer goodwill increases with the inflow of goodwill rate *GWR(t)* toward a target level determined by launch scale (see the launch scale management module). This process follows a typical formulation of goal-seeking behaviors in system dynamics modeling [31], modeled through a goodwill shortfall *GWSF(t)*, the gap between the current goodwill level *GW(t)* and target goodwill *TGW*, i.e., when the current level of customers' goodwill falls below target goodwill, efforts are made to increase goodwill, though such increase is subject to constraints of advertising budget BG_{ad}. Therefore, goodwill rate *GWR(t)* is defined as:

$$GWR(t)=Min\ (GWSF(t)/\tau_{gw}, BG_{ad}/C_{ad}) \quad (7)$$

$$GWSF(t)=Max(TGW-GW(t-1), 0) \quad (8)$$

Where *GWSF(t)* is goodwill shortfall, τ_{gw} is the time needed for advertising effort to generate goodwill, BG_{ad} is advertising budget, C_{ad} is the unit advertising cost, *TGW* is target goodwill, and *GW(t-1)* is the stock of customers' goodwill at time *t-1*.

3) Channel Management Module: This module models how launch decisions affect channel coverage. Similar to the adjustment of customers' goodwill, the development of channel outlets is guided by a target number of outlets determined by launch scale (see the launch scale module), following the typical goal-seeking behavior formulation [31]. The number of outlets increases with an outlet rate determined by the gap between the actual number of outlets and outlet target, subject to budget constraints set by launch scale (see the launch scale module). The outlet rate *OLR(t)* is defined as:

$$OLR(t) = Min\ (OLSF(t)/\tau_{ch},\ BG_{ch}/C_{ol}) \quad (9)$$

$$OLSF(t) = Max\ (TOL\text{-}OL(t\text{-}1),\ 0) \quad (10)$$

Where *OLSF(t)* is the outlet shortfall, τ_{ch} is the time needed for channel development, BG_{ch} is the available channel budget, C_{ol} is the unit cost of outlet development, *TOL* is the target number of outlets, and *OL(t-1)* is the total number of outlets at time *t-1*.

4) Manufacturing and Inventory Management Module: This module models the adjustment of production rate and production capacity (e.g. buildings and machines) based upon inventory level and product adoption. The structure of this module follows modeling traditions in manufacturing supply chain [31]. First, production is adjusted based upon inventory level. When the retailers' inventory level falls below current effective demand, an inventory gap is generated, and efforts are made to close the gap by increasing production order and correspondingly production rate [31] (P.714-715), [79] (The relationship between inventory gap and production order will be explained in the launch scale management module). Considering that production is constrained by the current production capacity, production rate *PDR(t)* is modeled as:

$$PDR(t)=Min\ (POD(t)/\tau_{pd},PCAP(t),) \quad (11)$$

Where *POD(t)* is production order made at time *t*, τ_{pd} is production delay, i.e., the time needed for the manufacturing process to complete, and *PCAP(t)* is production capacity.

Further, when production needs exceed production capacity, the difference between production order and production capacity creates a capacity shortfall, which necessitates acquisition of new capacity, subjected to budget constraint. Thus production capacity acquisition *CAPAQ(t)* is modeled as:

$$CAPAQ(t) = Min\ (CAPSF(t)/\tau_{cap}, BG_{cap}/C_{cap}) \quad (12)$$

Where *CAPSF(t)* is production capacity shortfall, τ_{cap} is the time needed to acquire new production capacity, BG_{cap} is the budget available for capacity development, C_{cap} is unit capacity cost. Capacity budget is determined by launch scale (see the launch scale module).

In addition, this module also includes the inventory transit process. Transit inventory refers to finished products before they reach the retailers, and it is modeled as the accumulation of the difference between production rate and the rate of product outflow from transit inventory to the retailers [31]. In sum, in this module, production is adjusted according to product adoption through the effort to close the inventory gap. As sales increase, inventory gap increases and requires production expansion to meet market demand.

5) Launch Scale Management Module: This module models how product launch scale affects the level of new resource commitment made to product launch in each period of the launch process (weekly). Launch scale ranges between 0 and1, with a higher value indicating more resource commitment. In the base model, launch scale is an exogenous variable, set before launch and stays unchanged during the launch process. Launch scale guides launch efforts by influencing targets such as target customer goodwill, target outlet, the size of production order, and the budget for launch activities such as advertising, channel development and production. Through these mechanisms launch scale ultimately influence production, adoption and sales.

Target goodwill, target outlet and production order are modeled as linear functions of launch scale[1]**.** Production order is determined by both the inventory gap and launch scale, because production order is driven by the need to close inventory gaps [31] (P.714-715), [79], as well as the need to meet future market demand forecasting [31] (P.710-716). When launch scale is high, not only more effort is

[1] We also tried nonlinear specifications including a diminishing return relationship modeled with a logarithm function and increasing return relationship modeled with an exponential function. With a logarithm function the influence of launch scale becomes less sensitive, and with an exponential function the influence of launch scale becomes more sensitive, but the simulation results stayed very stable. In the interest of parsimony, we used the linear formations in the model. This is consistent with practices in system dynamic modeling that suggest for areas of inquiry that have accumulated few attempts to understand the dynamics in a systematic fashion, simple models are needed [57]. We also tried similar nonlinear formulations for weekly budget and expected average sales and found similar results, and therefore we kept the linear formulation.

needed to close the inventory gap, but also production is increased to meet higher expected sales growth. Target goodwill, target outlet and production order are defined as follows.

$$TGW = a_1+b_1* LS \tag{13}$$

$$TOL = a_2+b_2* LS \tag{14}$$

$$POD(t) = INVGP(t) *(a_3+b_3* LS) \tag{15}$$

Where *TGW* is target goodwill, *TOL* is target outlet, *LS* is launch scale, *POD(t)* is production order, and *INVGP(t)* is inventory gap. b_1-b_3 are parameters that denote the linear influence of launch scale upon these targets. a_1-a_3 are assumed to be positive ($a_1, a_2, a_3>0$) because there is a minimum level of customer goodwill, channel outlets and production order that are not adjustable with launch scale. The marketing literature has found a certain level of customer goodwill exists without advertising effort (though decreasing over time), because past advertising efforts have extended effects upon customers' goodwill [76], [78]. For a new product, such goodwill comes from the firm's corporate brand image and previous advertising efforts on existing products. Thus, consistent with previous modeling effort, we expect a certain level of customer goodwill exists before new product launch and is not adjusted with current launch effort [18]. With regard to target outlet, a minimum amount of investment is needed to set up the distribution system to enable any product launch, for example, acquisition of a minimum number of channel outlets, hiring and training of a minimum number of salespeople, etc [5]. These are necessary despite of the level of launch scale (unless the new product project is terminated, which is not considered in this study). Lastly, a_3 is assumed to be positive because basic inventory management requires increase in production when inventory is not able to meet current demand despite of the influence of launch scale [31] (P.714-715), [79].

Meanwhile, launch scale also determines the amount of budget used to achieve these targets, thus affecting budgets for advertising, distribution channel and production capacity. Weekly budget increases with launch scale in a linear manner. As discussed above, a minimum budget is required for any level of launch scale because unless the product launch is terminated, certain spending is needed to keep the project going, for example, investments in minimum production and storage capacity, channel outlets and sales force, and expenses in managing the product launch, etc. [5]. Such spending is fixed and not dependent upon adjustments of launch scale. Thus weekly budget *BG* is defined as:

$BG = RBG * (LS + K)$ (16)

Where *LS* is launch scale, and *RBG* is a constant reference budget estimated by the managers prior to product launch. When launch scale =1, reference budget is fully utilized. *K* is the constant ratio of fixed minimum spending to the reference budget. For example, when *K*=0.5, an additional half of the reference budget is required to keep the operation going.

Lastly, launch scale determines the expected sales to be generated from the launch effort. Same as budget, expected average sales increases with launch scale in a linear manner.

$EAS = RS * LS$ (17)

Where *RS* is the reference sales estimated by the managers prior to product launch, and *LS* is launch scale. As the relationship between budget and sales can be very complicated, especially considering the budget includes investments in different activities such as advertising, distribution channel, production capacity and inventory management, it is difficult to define a function for such a relationship without causing any bias. Thus, we took an approach that does not explicitly specify this relationship, but allow estimates of budgets and expected sales to be formed before launch. This is a reasonable assumption because although the new product launch process is highly uncertain, managers usually use their marketing knowledge and previous experience to form rough estimates of the average marketing and manufacturing spending needed and the corresponding sales expected from such spending [5], [80]. Thus, before product launch a reference budget and reference sales are set. In this model, the reference budget is set at $500,000 per week, and the reference sales are 5000 units per week.

6) Price Management Module: This module models how the market price is set for a new product. Following a cost-based penetration pricing strategy, a desired price is calculated from estimated unit product cost with a percentage markup [81].

$DP(t) = (EUMMC + UVC(t))*(1+c) \qquad (0 < c < 1)$ (18)

Where *DP(t)* is the desired price at *t*, *EUMMC* is the estimated unit marketing and manufacturing costs, *UVC(t)* is the unit variable cost, and *c* is a constant markup percentage.

Unit marketing and manufacturing cost is estimated by dividing weekly budget on advertising, channel development, production capacity and inventory management, by the average weekly sales (in units sold) expected to be generated from such budget.

$$UMMC = BG/EAS \tag{19}$$

Where *BG* is weekly budget and *EAS* is the weekly expected average sales. Budget and expected sale are used instead of actual spending and sales because prices are set before launch when no actual spending occurs and no sales information is available [81]. Thus managers usually have to rely on estimates to determine the price. In static launches, because launch scale is fixed, weekly budget, expected average sales, and the estimates of unit marketing and manufacturing cost are also not adjustable. In dynamic launches where launch scale can be adjusted weekly, the influence of actual spending and sales on cost is incorporated through the feedback from sales to launch scale and budget.

Based on the desired price, actual market price is adjusted at the following rate:

$$PR(t)= (DP(t)-P(t-1))/\tau_p \tag{20}$$

Where *PR(t)* is the price adjustment rate, *P(t-1)* is the market price at time *t-1*, *DP(t)* is the desired price at time *t*, and τ_p is the time needed to adjust price.

7) Accounting Management Module: The accounting management module calculates costs, revenue, and total profit (Figure 3). Total cost accumulates weekly and includes fixed cost (channel spending, advertising spending, capacity spending and inventory cost) and variable cost. Unit cost is calculated by dividing total cost by production volume. As unit production costs usually decrease as production scale increases and the firm gains more experience, unit variable cost *UVC(t)* is modeled to decrease with total production [82], [83].

$$UVC(t) = IVC - PD(t)*g \qquad (0<g<1) \tag{21}$$

Where *IVC* is the initial variable cost, *PD(t)* is total production at time *t*, and *g* is a constant between 0 and 1 that denotes the rate of marginal cost reduction.

Total profit *PROF(t)* is the accumulation of weekly profit determined by adoption rate *ADOP(t)*, market price *P(t)* and unit costs *UC(t)*:

$$PROF(t) = \int_0^t (P(t) - UC(t)) * ADOP(t) \quad (22)$$

Insert Figure 3 here

In summary, the base model elaborates the mechanisms through which launch scale dictates launch tactics such as advertising, channel development, manufacturing and inventory management and pricing, and ultimately influence product adoption and sales (Figure 4). Launch scale not only determines the efforts of advertising and channel development by setting targets and budgets, and also influence production by adjusting the firm's effort to close inventory gaps. Through these loops, launch tactics are adjusted to meet the requirement of overall launch scale. Meanwhile, the model incorporates two short-term adjustment loops based upon feedbacks from product sales. First, as sales increase, inventory gap increases and leads to production expansion, which in turn reduces the inventory gap. Through this loop, production is adjusted according to actual product sales. Second, as the production scale increases with sales, product unit cost is reduced and a lower price is charged to attract more sales. The cost reduction and pricing loop further boost product adoption in addition to advertising and distribution efforts, and it reflects the economy of scale and the benefit of aggressive launch efforts. These short-term adjustments reflect the coordination among different launch tactics, but they are within the extent of the predetermined launch scale that stays unchanged during the launch process.

Insert Figure 4 here

C. The Dynamic Model

The dynamic launch model is a modification of the base model by allowing adjustment of the launch scale over time. In this model, launch scale is endogenous and modeled as a stock variable that is adjusted according to the managers' perception of actual market conditions based on launch performance. The feedback relationship between performance and continued resource commitment is supported by both theories and modeling practice [53]. New product launch literature also suggests that as product launch effort starts to generate sales, managers form understandings of the actual market condition based upon actual product adoption rate, which the guides the managers further launch actions [5], [49].

The managers' understanding of actual market conditions is not solely based upon actual sales, but the comparison of actual adoption rate to the expected sales at a certain time point [5], [49]. This is also consistent to behavioral theories that argue customer satisfaction is a function of actual experience and expectations [84], [85]. If adoption rate is higher than expected sales, it indicates that the market condition is highly responsive, i.e., launch effort is able to effectively generate sales. On the other hand, if adoption rate is lower than expected sales, it indicates that the market condition is not as responsive as expected.

We formulate the model for dynamic adjustment of launch scale based upon Repenning's model of innovation implementation [53] and Urban and Hauser's [5] (P. 541) description of new product launch control system. Two key loops determine the adjustment of launch scale (Figure 5). The positive reinforcement loop represents the process where launch scale dictates tactical activities such as advertising, channel development, production and pricing to increase product sales, and increased product sales in turn motivate the managers to increase resource commitment to the launch. The balancing loop indicates that higher launch scale also raises the managers' expectation of sales [5], [49], which lowers their perception of how responsive the market is. Less responsive market conditions will reduce the managers' future resource commitment to the product launch, thus reducing future sales. We use a variable p*erceived market condition* to represent the managers' understanding of actual market conditions. Specifically:

$$PMC(t) = ADOP(t)/CES(t)-1 \quad (23)$$

Where *PMC(t)* is perceived market condition, *ADOP(t)* is the actual adoption rate, and *CES(t)* is the current expected sales, which is estimated from weekly expected average sales *EAS(t)* assuming expected sales grow in a linear manner from week 12 to week 1000[2].

When *PMC(t)* >0, it indicates the market is more responsive than expected, i.e., marketing effort is able to generate more sales than expected, therefore launch scale should be increased to fully

[2] This is a simple way to model the fact that managers expect new product sales increases as time goes by. Though in reality the functional form may not be a linear one, the linear functional form is sufficient for the current use in the model.

utilize market opportunity; when $PMC(t)<0$, it indicates the market is less responsive than expected and launch scale should be reduced to avoid waste of investments. Thus based upon the perceived market condition, launch scale *LS* is adjusted at the following rate:

$$LSR(t) = PMC(t-1)*LS(t-1)/\tau, \quad (24)$$

This adjustment process is delayed by *patience time* τ because management decisions are usually delayed due to information delays, managers' patience and confidence with their prior judgments, and organization inertia [86], etc.

Insert Figure 5 here

V. ANALYSIS

This study takes a medium-term perspective (i.e., about 5-6 years from the start of the launch). A short term is not enough to study the dynamic nature of the new product diffusion process; a long-term approach that covers a product's entire product life cycle is also not appropriate as a new product loses its newness after it reaches the mature stage of its life cycle. The time unit of the simulation is week, and the total simulation period is 300 weeks (6 years, assuming 50 working weeks per year). The first 12 weeks of a simulation are the pre-launch periods, during which initial product capacity is acquired, initial inventories are produced, and channels are developed based on policy targets and budgets that are determined by launch scale. Sales of the new product start in the 12th week. Total profit for the new product is used as the criterion for evaluating the performance of launch strategies because for most firms, the ultimate goal for new product launch is profit. Profit is also the most appropriate medium-term performance measure.

The values of parameters used in the simulation are presented in Appendix A. The total market potential of the new product is set at 1,000,000 units of sales. Prior to the launch the managers' estimate of reference sales is 5000 units/week on average, and the estimate of reference budget for fixed marketing and manufacturing cost is $5,000,000. Price is estimated based upon the fixed and variable costs with a 20% markup. While it may be helpful to simulate the model with a real new product launch, such approach is not often used in simulation of system dynamics models [51]-[54]. Our approach is consistent with existing practices in system dynamic modeling and avoids the constraints of a specific product context and allows a more generalizable interpretation of the model. To ensure the robustness of simulation results and understand the influence of parameter values on model behavior, we conduct sensitivity analysis for the model parameters after presenting the simulation results.

Before evaluating the performance of dynamics launch strategies under different market conditions, we first examined the behavior of the base model. The simulation results of the base model can serve as a validation of the model formulation because if the model behavior is consistent with existing understandings and replicates the new product launch process well, it indicates this model sufficiently captures the key elements of new product launch and the dynamics among these elements [31] and it lends confidence to extending the model to examine dynamic launch strategies. We ran the base model under high and low levels of market responsiveness, i.e., when the exogenous variable *market responsiveness* was set at 0.8 and 0.2 respectively. To ensure the robustness of the results, we also ran the model with high and low market responsiveness set at 0.9 and 0.1 respectively, and 0.7 and 0.3 respectively. Similar results were obtained. A launch scale of 0.8 is used to represent a fat launch strategy and 0.2 for a narrow launch strategy.

A. Static Launch Strategies and Validation of the Model

1) Scenario 1: High Market Responsiveness: Figure 6 shows the simulation results for narrow and fat launch strategies under high market responsiveness. Both launch strategies show a product S-shaped diffusion curve consistent to the Bass model [59] [60] [70] and the total profit grows over time as product adoption increases. Meanwhile, unit cost is reduced as more products are produced and sold to share the fixed manufacturing and marketing cost, and the low cost in turn allows the firm to charge a lower price. Thus the results on unit cost and price are also consistent with theories of cost reduction and production experience curve [82], [83].

A comparison of the two launch strategies shows fat launch strategy clearly leads to a more rapid diffusion process, reaching the peek at about week 360 with a peak adoption value around 2300 products/week. The diffusion curve for narrow launch strategy is rather flat, reaching its peak at around week 700 with a peak value around 1000 products/week. With regard to total profit, though narrow launch strategy loses less money at the start and achieves profitability slightly earlier than fat launch strategy, the total profit for fat launch strategy increases far more sharply and clearly exceeds that of narrow launch strategy at week 120. At the end of week 300, the total profit for fat launch strategy is significantly higher than that of narrow launch strategy.

The fat launch strategy's superior performance is driven by its aggressive launch effort such as advertising and channel development, which accelerate the diffusion process greatly and generate more sales. The higher sales and production scale also further reduce product unit cost and allow the firm to boost market demand with a lower price. Fat launch strategy generates a lower profit margin and relies on large sales volume and quick cost reduction to achieve profitability. When market is highly responsive, the low profit margin is able to produce high profit due to high market demand. The relative performance of narrow and fat launch strategies is also consistent with marketing theories [49] and predictions developed in the introduction section.

2) Scenario 2: Low Market Responsiveness: Figure 7 shows the simulation results for narrow and fat launch strategies under low market responsiveness. The adoption rate for fat launch strategy is still much greater than that for 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. With regard to total profit, narrow launch strategy outperforms fat launch strategy considerably. At week 300, fat launch strategy is still at a net loss, while narrow launch strategy produces a profit.

In this scenario, even though the adoption rate for fat launch strategy is higher than narrow launch strategy, it is not high enough to compensate for fat launch's disadvantage of low profit margin. The market is not responsive to fat launch strategy's heavy commitment to advertising and the resources are largely ineffective and wasted. On the contrary, narrow launch strategy commits only very few new resources and charges a higher price. It benefits from a larger profit margin rather than rely on fast cost reduction brought by large sales volumes. Thus such strategy is able to stay profitable when the market is not responsive and sales growth is low.

In sum, the behavior of the base model under both high and low market responsiveness is consistent with existing understanding of the product launch process. Both fat and narrow launch strategies show an S-shaped product diffusion curve consistent to the Bass model and other empirical evidence [59], [60], and the total profit grows over time as product adoption increases. The over time change of unit cost and price during the launch process is also consistent with theories of cost reduction and production experience curve [82], [83]. And the relative performance of narrow and fat launch strategies is consistent with predictions of marketing theories [49]. This indicates the model sufficiently captures the key elements of new product launch and the dynamics among the strategic and tactic elements such as launch scale, advertising, pricing, manufacturing, and channel management, etc., thus providing support for the validity of the model.

Insert Figure 6 and 7 here
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3) Findings from the Base Model: The results from the base model show fat launch strategies are more effective when market is highly responsive and narrow launch strategies are more effective under low market responsiveness. These results indicate static launch strategies can only be successful when actual market conditions are the same as pre-launch forecast. They are not able to effectively manage the market uncertainty associated with new product launches. The results also demonstrate that without adjusting product launch scale, short-term adjustments at the tactical level (that is, at the individual functional level) are rather ineffective for optimizing the entire new product launch process.

B. Dynamic Launch Strategies

In dynamic launch strategies, launch scale is allowed to be adjusted according to actual market conditions. The initial launch scale is set at 0.5 under both high and low market responsiveness.

1) Scenario 1: High Market Responsiveness: Figure 8 shows the simulation results for dynamic launch strategies under high market responsiveness. Starting from the initial value of 0.5, launch scale is increased and quickly exceeds the launch scale of fat launch strategy (0.8). It reaches the maximum value of 1 and stays there until around week 290 when it starts slowly decreasing as the adoption rate reaches its peak and starts to decrease. Production rate and other launch tactics are also adjusted accordingly (only production rate is presented). In presence of high market responsiveness, quickly increasing launch scale at the early stage of the launch generates high market demand and enables new product diffusion to take off much faster. When adoption rate slows down, launch scale is dynamically adjusted down, reducing unnecessary new resource commitment at later stage. Thus dynamic strategy not only generates higher total profit than narrow launch strategy, but also outperforms fat launch strategy because it is able to penetrate the highly responsive market.

2) Scenario 2: Low Market Responsiveness: When market responsiveness is low, dynamic launch strategy is able to adjust launch scale quickly to lower values and reduce resource commitment to match the actual adoption rate (Figure 9). Starting from the initial value of 0.5, launch scale quickly adjusted down to the level of a narrow launch strategy (0.2), and as market is not responsive it is further reduced to below 0.2. Although dynamic launch strategy does not generate more product adoption than fat or narrow launch strategies, it is able to keep a profitable profit margin by keeping resource commitment low. As a result, at the end of the product launch period, dynamic strategy is able to achieve higher total profits than both fat and narrow launch strategies. The total profit of dynamic launch strategy only exceeds that of narrow launch strategy after a period of time (week 225) because time is needed for the initial launch scale to adjust down. Narrow launch strategy is set at a launch scale (0.2) more proper for an unresponsive market and is more profitable until dynamic strategy is able to adjust its scale down for the initial level of 0.5. While launch scale can be adjusted up quickly in a highly responsive market, downward adjustment is less sensitive and takes more time. This is because there is a limit to lowering launch scale due to the minimum expenses needed to keep the launch project going. Investments in marketing and manufacturing can also be rigid to downscaling as advertising and distribution contracts may not be able to terminate quickly and managers may be reluctant to vacate production facilities.

Insert Figure 8 and 9 here
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3) The Effects of Initial Launch Scale: In dynamic launch strategies, launch scale can be adjusted to unexpected market conditions, but managers still need to determine an initial launch scale prior to launch based upon forecasts. Does initial launch scale still matter in dynamic launch strategies? We examine the effects of the initial launch scale in dynamic launch strategies under the scenarios of high and low market responsiveness.

Figure 10 shows the simulation results under high market responsiveness when initial launch scale is set at high (0.85), medium (0.5) and low (0.15) levels. Even though the strategy with fat initial launch scale best fits the market conditions, the strategy with medium initial launch scale is able to quickly 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, consequently realizing lower total profit. These differences indicate that pre-launch forecasts and selection of initial launch scales are still very important for dynamic launch strategies. However, dynamic launch strategy is robust enough to alleviate mistakes in pre-launch forecasts and initial launch decisions.

The robustness of dynamic launch strategies is also supported under low market responsiveness (Figure 11). Dynamic launch strategies with different levels of initial launch scales were all able to quickly lower their resource commitment, thus reducing unnecessary costs. Due to different levels of sunk costs at the initial stage of product launch, strategies with higher initial launch scale achieved lower total profit. Though higher initial launch scale leads to relatively higher adoption rates, the difference is too small to recover from wasteful resource commitment at the initial stage.

Insert Figure 10 and 11 here
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4) Findings for the Dynamic Model: Results from the dynamic launch model support the key argument that under high market uncertainty, product launch scale needs to be adjusted dynamically according to actual market conditions. Specifically, we find: (1) Dynamic launch strategies are superior to static launch strategies as it can dynamically adjust resource commitment and launch efforts to match changing market conditions. (2) Pre-launch market forecast is still an important factor for launch success in dynamic launch strategies. (3) Unlike static launch strategies, dynamic launch strategies are able to correct poor pre-launch forecasts and initial launch decisions, as it can quickly move away from initial launch scale and adapt to actual market conditions.

C. Sensitivity Analysis

To further examine model behavior and robustness of findings, we conducted sensitivity analysis for the model parameters. Due to the large number of parameters, instead of analyzing all parameters simultaneously, we grouped the parameters into five groups related to (1) references set up by the managers, (2) costs, (3) market demand, (4) launch scale, and (5) time delays (Appendix A), and conducted multivariate sensitivity analysis for each group. Since there is no clear evidence to assume other forms of distribution for the model parameters, we used a random uniform distribution for all the parameters [87], and tested for parameter values within the range from 25% below to 25% above the current parameter value [31] (P.886).

To verify whether the relative performance of different launch strategies is a robust finding, we formed a variable representing the difference in the total profit generated by different launch strategies. For example, to compare fat and narrow launch strategy under high market responsiveness, the difference is the total profit of fat launch strategy minus the total profit of narrow launch strategy, and if our findings are robust, this difference should be consistently above zero despite different parameter values. The results for sensitivity analysis are presented in Appendix B.

We first compared the performance of static launch strategies under high (Figure 1 in Appendix B) and low (Figure 1 in Appendix B) market responsiveness. For high market responsiveness, the Y axis represents the extent to which fat launch strategy generates more profit than narrow launch strategy, and for low market responsiveness the Y axis represents the extent to which narrow launch strategy generates more profit than fat launch strategy. The results show that when the market is highly responsive, fat launch strategy always outperforms narrow launch strategy, but when the market is not responsive, narrow launch strategy always outperforms fat launch strategy, thus providing support to the robustness of our findings about static launch strategies.

Then we compared the performance of dynamic launch strategy and fat launch strategies under high market responsiveness (Figure 3 in Appendix B), and the performance of dynamic launch strategy and narrow launch strategies under low market responsiveness (Figure 4 in Appendix B). The model behavior stays stable and dynamic launch strategies consistently outperform fat and narrow launch strategies under different market conditions. Thus the sensitivity analysis provides support to the robustness of our findings about dynamic launch strategies.

To examine the sensitivity of the model to individual parameters, we conducted univariate sensitivity analyses for each parameter. Similarly, we looked at the difference in the total profit generated by different launch strategies, and tested for parameter values within the range from 25% below to 25% above the original parameter value. While all of the univariate sensitivity analyses supported the robustness of the findings, i.e., when market is highly responsive, fat launch strategy outperforms narrow launch strategy; when the market is not responsive, narrow launch strategy outperforms fat launch strategy; and dynamic launch strategies consistently outperform fat and narrow launch strategies under different market conditions, a few parameters produced a larger range of variation in the difference between the total profits generated by different strategies (Due to limited space, the sensitivity analysis graphs are not presented for individual parameters but can be obtained from the authors).

Among all the reference related parameters, reference sales and reference budget produced larger variations. Under high market responsiveness, when reference sales varied in a (-25%, 25%) range of its original value, the total profit difference between dynamic and fat launch strategy varied in a (-53%, 69%) range of the original profit difference; when reference budget varied in a (-25%, 25%) range, the total profit difference varied in a (-58%, 51%) range. While the total profit difference still indicates dynamic strategy outperforms fat strategy, the difference in the performance varies with the reference sales and reference budget set up by managers. This highlights the importance of managerial expectations of sales and budget, because such expectations influence the managers' perception of how responsive the actual market condition is and thus influencing the adjustment of launch scale.

As for parameters related to launch scale, patience time (τ) generated a larger variation in the profit difference between dynamic and narrow launch strategies (a range between -47% and 61%) under low market responsiveness, but not under high market responsiveness. The model's sensitivity to patience time under low market responsiveness indicates the importance of quickly adjusting down launch scale to cut loss when the market is not responding to marketing efforts. While failing to quickly increase launch scale causes delay in the realization of market opportunities, not being able to quickly reduce launch scale under bad market conditions directly leads to financial loss. While managers tend to be more ready to increase launch effort and reluctant to reduce launch scale, our results show in fact taking quicker actions to reduce launch scale when the market is not responding is more critical. The parameters related to cost, demand and time delays did not produce large variations.

VI. DISCUSSION

A. Theoretical Contributions

This study examines the behavior of dynamic launch strategies that allow adjustments of launch scale according to actual market conditions. The intrinsic market uncertainty associated with new products brings great risk to new product launch. With a system dynamics model, this study illustrates how dynamic launch strategies are able to adapt to changing market conditions and correct inaccurate pre-launch forecasts. These findings provide support for the importance of strategic flexibility and suggest allowing such flexibility in pre-launch strategic planning is critical for new product launch success, especially when the product is really new and faces high market uncertainty.

More importantly, by formalizing the feedback dynamics through which new market information is absorbed in dynamic launch, this study contributes to our understanding of new product launch strategies by illustrating why and how dynamic approaches outperform static ones. The nature of system dynamics modeling determines its approach to deliver new insights is to develop understandings of the phenomenon by analyzing the structures that create the processes of feedback loops [31], [57]. Although the literature recognizes the importance of flexibility in new product launch, existing understanding is limited to a fairly general concept and there have been few attempts to understand the dynamics in a systematic way. Our system dynamic model formalizes an integrated system that incorporates important feedback relationships during new product launch, thus revealing some important insights that have not been well understood in the literature.

First of all, existing research lacks a clear understanding of the specific types of over time adjustments required for a dynamic approach of new product launch. While many adjustments can occur during the launch process, short-term adjustments and long-term adjustments play distinct roles. Though short-term adjustments, including altering production and inventory to meet sales growth or reducing price as sales grows and cost decreases, are also based upon feedbacks from actual sales, they react to product sales rather than actively influence sales. Long-term adjustments on the other hand, proactively influence sales by changing overall launch scale and correspondingly advertising and distribution effort. While existing research does not distinguish between different levels of adjustments, our model shows a fundamental difference between short-term adjustments and long-term adjustments. Short-term adjustments coordinate among marking mix variables and are important part of new product launch management. However, that fact that static strategies that include short-term adjustments do not perform well under market uncertainty suggests that the extent to which short-term adjustments can respond to market demand is limited and it is not likely to make a launch successful if the pre-launch forecast is inaccurate. Given high level of market uncertainty, long-term adjustments, i.e., the change of overall launch scale, is necessary to proactively manage marketing investments to influence demand and sales. Thus a true dynamic launch strategy needs to go beyond short-term adjustments to incorporate adjustments of marketing effort at a strategic level.

Secondly, existing research lacks a profound understanding of the mechanism through which launch scale is adjusted. This study formalizes the mechanism of launch scale adjustment based upon managers' perceptions of actual market condition, and illustrates a specific dynamic approach to resource commitment that can increase profitability. This dynamic approach is to adjust resource commitment based upon the comparison between actual market sales and expected sales, increasing resource commitment when the market is more responsive than expected and reducing resource commitment when the market is less responsive than expected.

The dynamics of launch scale adjustment highlights the key role of managers' perceptions of actual market conditions in such adjustment. The managers' perception of actual market condition is not solely based upon actual sales, but formed through the comparison of actual sales to their expectations of sales. Launch scale not only increases the launch efforts, but also raises the managers' expectations of product sales, which lowers the managers' perception of actual market condition given the same level of actual sales. This indicates it is critical for managers to form reasonable expectations and make adjustments of the expectations over time as actual market conditions unfold. Our dynamic model allows not only adjustment of launch efforts but also the managers' sale expectations according to updated sales information, which constitutes a truly dynamic new product launch process.

To improve the understanding of changing market conditions and update sales expectations, explicit procedures and tools are needed to periodically evaluate market responses and future return of launch investments. Just as any other investment, new product launch is the management of resource commitment and future return. Large investments can only be profitable when it generates enough sale volume to compensate for the low profit margin. A real options approach has been proposed to evaluate of future payoffs product development projects [43] [44]. The same approach can be applied to new product launch to evaluate the value of different launch scales. Incorporating dynamic adjustments and interactions of different tactical launch elements, our model can be applied as a simulation tool to evaluate future return of launch investments at a given point of time.

The important role of managers' perception of market conditions also highlights the need to study the behavior of new product managers. Perception of market conditions is formed within the context of the managers' individual knowledge and experience, and influenced by their personality traits and management style. New product research would benefit from a behavioral perspective that investigates the role of new product managers in dynamic process of new product launch.

Lastly, this study develops an integrated framework of new product launch that incorporates both marketing and supply chain management perspectives. It demonstrates supply chain management is an integrative part of new product launch strategy, suggesting the need for future new product launch research to consider the role of supply chain activities and their interactions with the marketing activities. By formalizing interactions and coordination among different tactical activities, the model provides implications for efficient combination of resources in different marketing and supply chain activities that is beneficial for launch profitability.

B. Methodological Contributions

This study makes important mythological contributions to the field of new product development. It developed and validated a first-of-its–kind system dynamics model that incorporates several dynamic processes: the new product diffusion process, the marketing response process and the supply chain management process (i.e. ordering fulfillment, inventory management and manufacturing). This model provides a platform that can be easily extended to investigate many more complicated issues in new product launch such as adjustments to environmental shock, reactions to market competition, etc. By adopting a system dynamics methodology, this study provides a new approach for modeling new product launch process that enables us to examine the dynamic interactions among the strategic and tactical elements in the launch process.

C. Managerial Contributions

This study provides several important insights on managing market uncertainty for new product launches. First of all, firms can benefit from building in flexibility in pre-launch strategic plans, especially when market uncertainty is high. Due to rigidity in launch tactics, especially channel and manufacturing systems, adjustments after initial launch is difficult unless flexibility has been incorporated in the strategy before launch. The Spanish clothing company Zara is known for its flexible new product launch strategies that allow clothing lines that sell well to be manufactured and delivered at a higher volume and lines that do not sell pulled back from the market [88]. Such quick response is supported by pre-launch planning that sets up flexible manufacturing and supply chain systems. Building flexibility in manufacturing and supply chain not only involves technological challenges but also has important implications for the design and management of the supply chain. Highly integrated supply chain or long-term stable partnerships with suppliers may be necessary to obtain quick reactions to customer demand, and effective information systems can also enhance communication and response speed. Given that strategic planning is often not carried out very well in practice [67], a deeper understanding of these issues helps managers develop better management philosophy and practice in organizing the process and people in product launches.

Secondly, our model shows that dynamic new product launch requires frequent evaluation of market conditions. Thus, explicit procedures and tools of such evaluation would benefit decision making in product launch. Although such approaches have been applied in new product development (e.g., the stage gate process), assessment of market conditions in new product launch often lacks explicit procedures or tools of updating estimates of market responsiveness and future returns of launch investments. Development of procedures and tools of simulating the input and output of new product launch to form better estimates would greatly facilitate decision-making.

Lastly, the system dynamics model developed in this study can be used as a “flight simulator” in managerial training. Used as a simulation tool, the model can help new product managers understand the dynamic interactions among different elements in new product launch and the feedback dynamics during the adjustment of launch scales in response to new information on market demand. The integrative nature of the model also allows illustration of the interactions between marketing elements and supply chain elements, which is consistent with the cross-functional nature of new product launch. The model can also illustrate different scenarios in a new product launch and help managers form evaluations of future return of launch investments based upon the scenario analysis.

D. Limitations and Future Research

One of the limitations of the study is that we only considered traditional advertising not other marketing techniques such as viral and e-marketing. While these new marketing techniques play an important role [68], we restricted the model to traditional advertising due to the size and complexity of the model. Future research that extends this model to consider these techniques would enhance our understanding of the role of marketing in dynamic new product launch. Further, in this study market uncertainty is only modeled with high versus low levels of market responsiveness. More complicated models of market uncertainty can be examined to test the robustness of the model and findings. Third, the current model can be extended to incorporate other elements such as market competition and used to investigate more complicated dynamics of new product launch. Lastly, our findings indicate that in dynamic launch strategies launch scale seems to adjust up faster and more effectively than adjust down due to rigidity of investment downscaling. Future research that models this asymmetric effect would enhance our understanding of dynamic launch strategies. In sum, as a first attempt to bring system dynamic modeling to new product launch research, this study provides a model that allows examination of dynamic feedbacks during new product launch, and this model provides a platform that can be easily extended in future research to investigate complex interactions of various factors impacting new product launch.

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TABLE I
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

TABLE II
RESEARCH DESIGN

		Scenarios	
		High Market Responsiveness	Low Market Responsiveness
Static Launch Strategies	Fat Launch		
	Narrow Launch		
Dynamic Launch Strategies	Dynamic Launch		

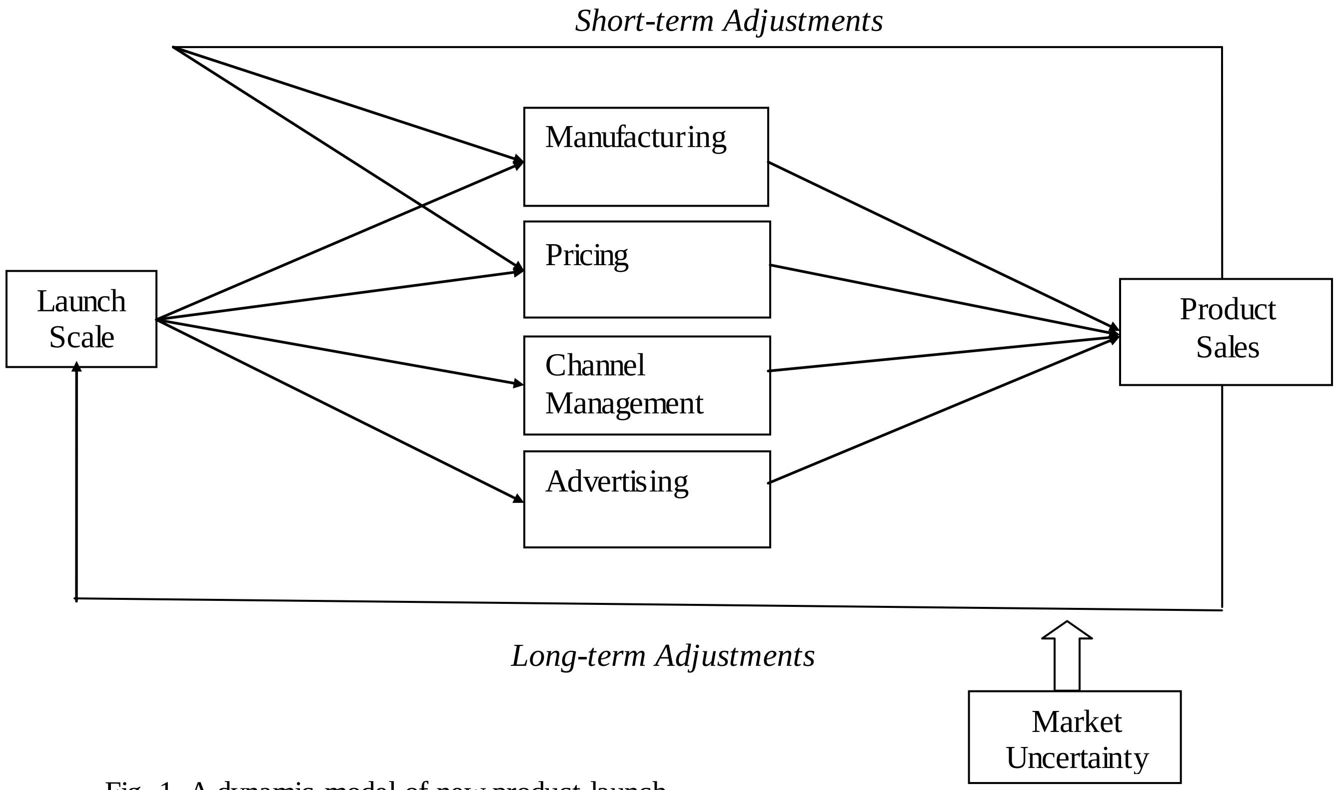


Fig. 1. A dynamic model of new product launch

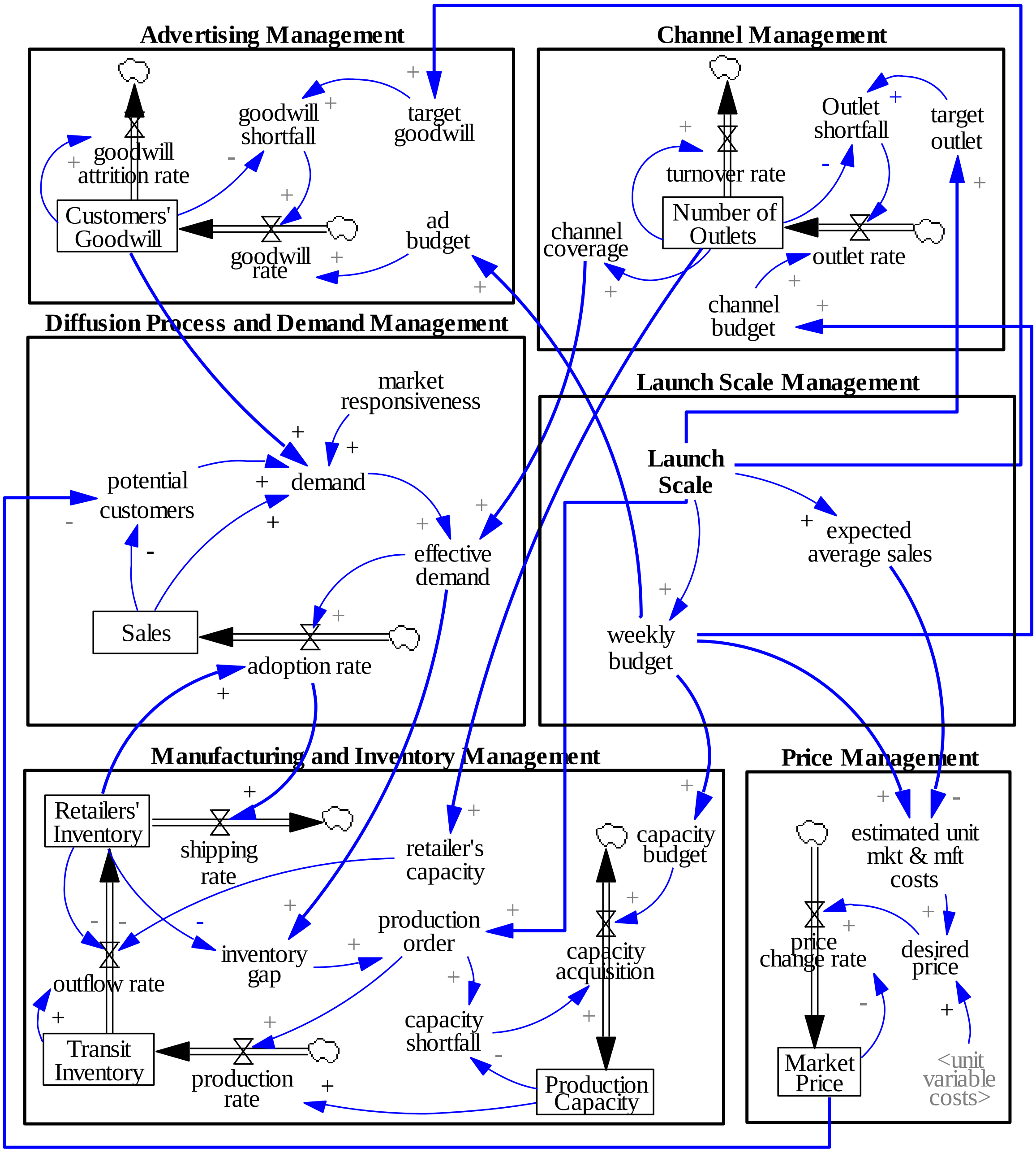


Fig. 2. The base model

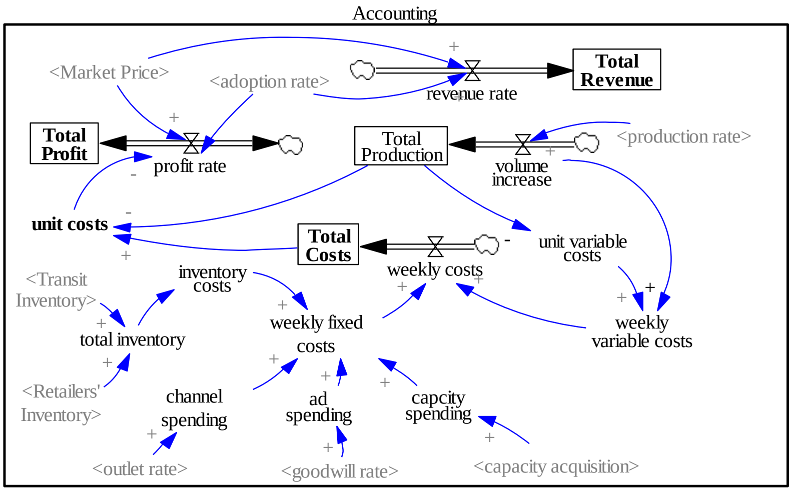


Fig. 3. Accounting module

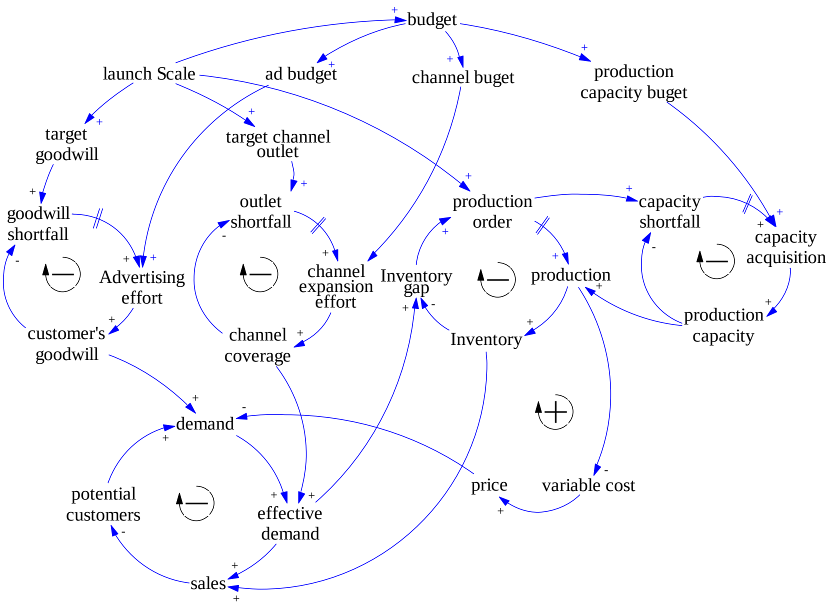


Fig. 4. Simplified causal diagram for the base model

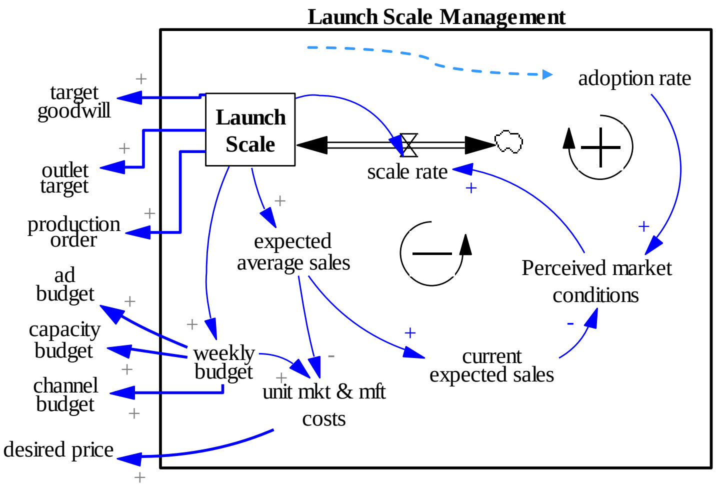


Fig. 5. Launch scale management: dynamic model

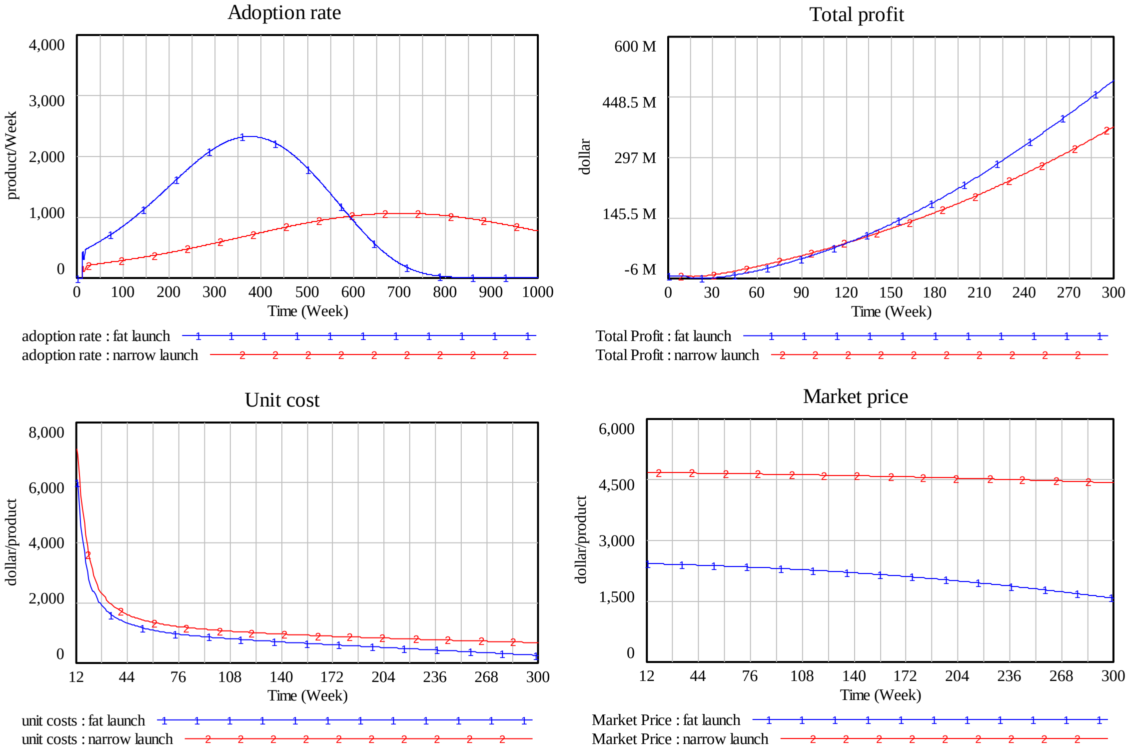


Fig. 6. Simulation results for static launch strategies under high market responsiveness

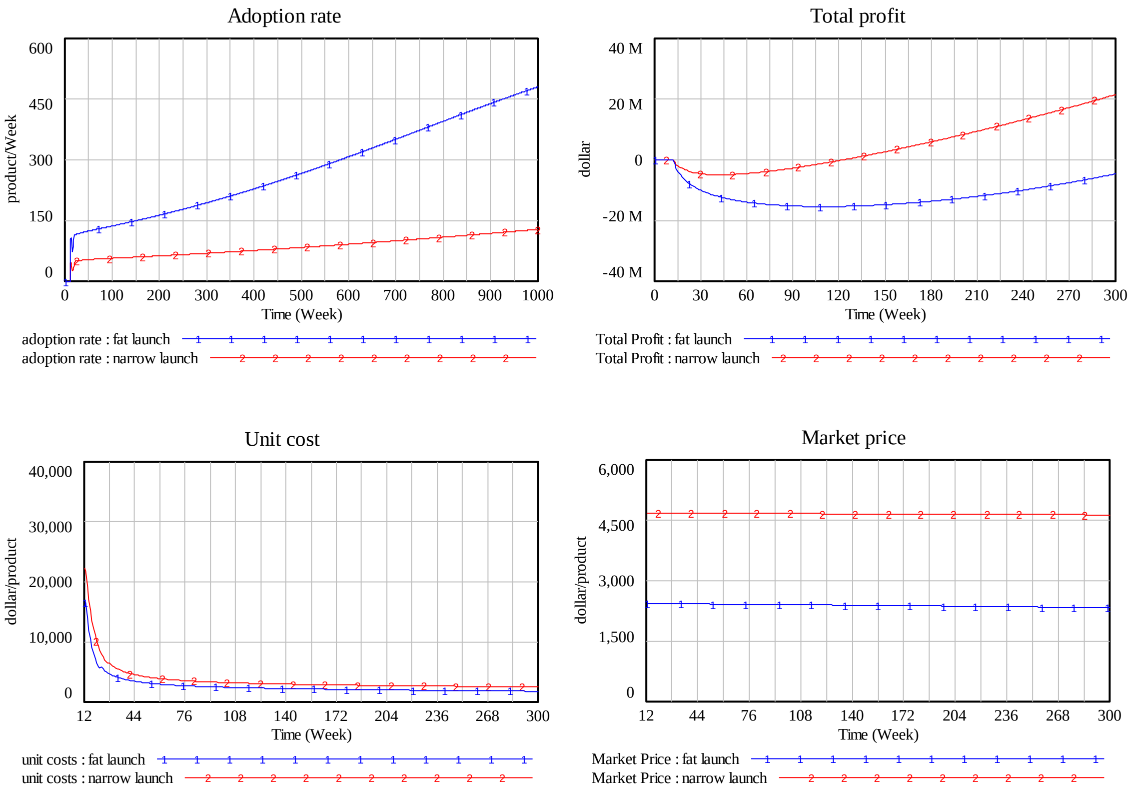


Fig. 7 Simulation results for static launch strategies under low market responsiveness

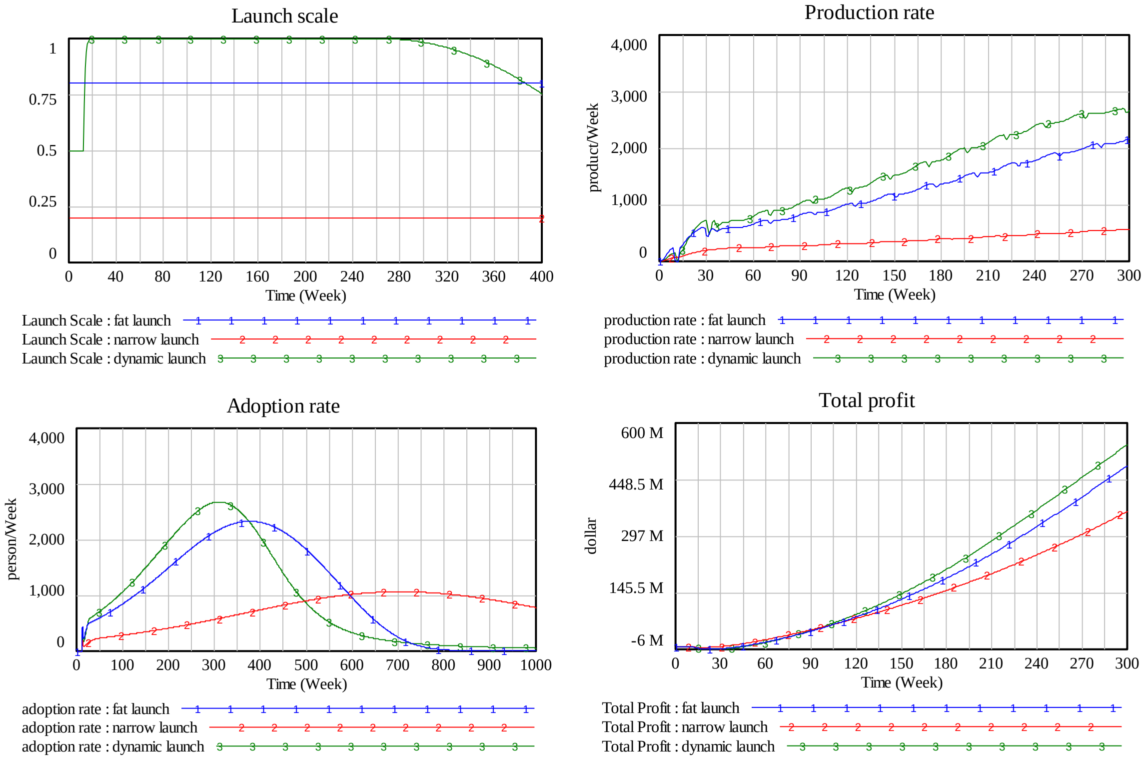


Fig. 8. Simulation results for dynamic launch strategy under high market responsiveness

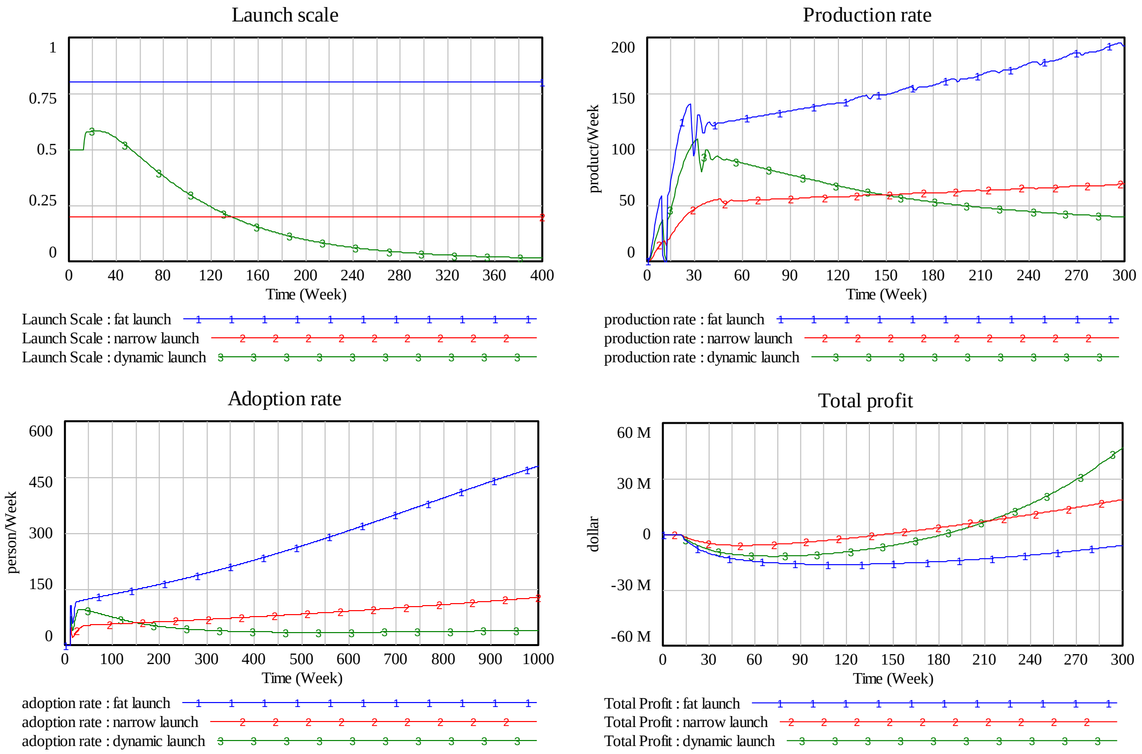


Fig. 9. Simulation results for dynamic launch strategy under low market responsiveness

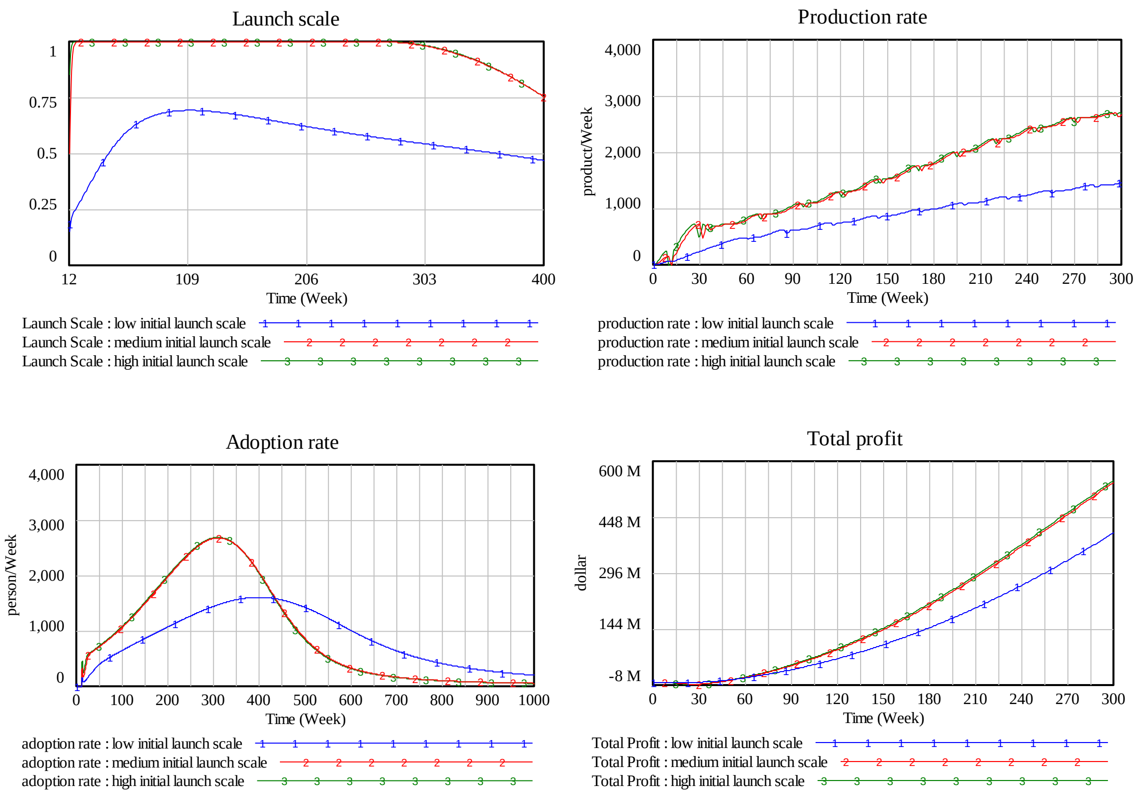


Fig. 10. The effects of initial launch scale under high market responsiveness

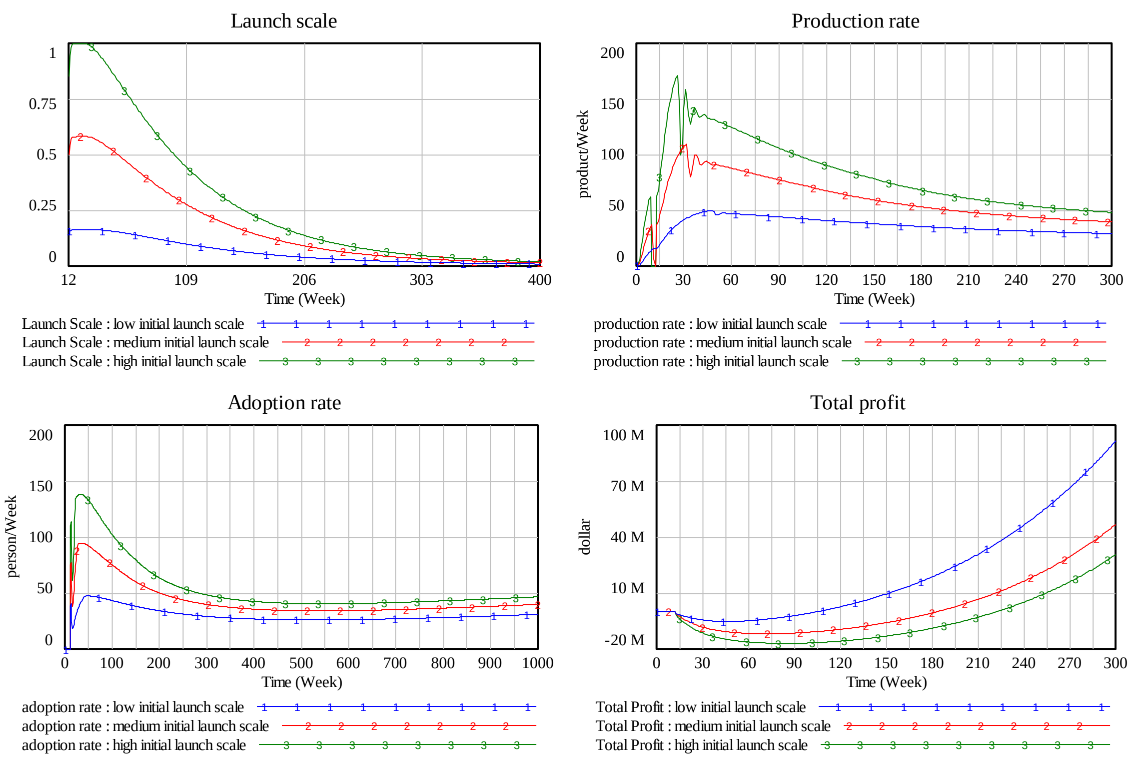


Fig. 11. The effects of initial launch scale under low market responsiveness

Appendix A. Parameters in the model

Symbol	Parameter	Value
1. References		
RS	Reference sales	5,000
RBG	Reference budget	5,000,000
RP	Reference price	1,700
RD	Reference demand	1,000,000
2. Costs		
IVC	initial variable cost	400
C_{ad}	unit advertising cost	2,000,000
C_{cap}	unit capacity cost	8,000
C_{Ol}	unit outlet cost	500
C_{in}	unit inventory cost	0.025
g	marginal cost reduction	0.002
3. Demand		
d	Demand elasticity	-0.3
p	External effect coefficient	0.001
q	Internal effect coefficient	0.015
c	Price markup	0.2
u	Unit outlet capacity	200
4. Launch scale		
a_1	Coefficient of target goodwill	0.4
b_1	Coefficient of target goodwill	0.6
a_2	Coefficient of target outlet	4,000
b_2	Coefficient of target outlet	6,000
a_3	Coefficient of production order	4
b_3	Coefficient of production order	6
K	Coefficient of fixed minimum spending	0.5
5. Time delays		
τ_{gw}	goodwill delay	2
τ_{tr}	transit delay	2
τ_{pd}	production delay	2
τ_{p}	price delay	4
τ_{iv}	desired inventory coverage	2
τ_{tn}	turnover time	30
τ_{cap}	production cap time	30
τ_{ch}	channel dev time	30
τ	patience time	65

APPENDIX B. Sensitivity analysis

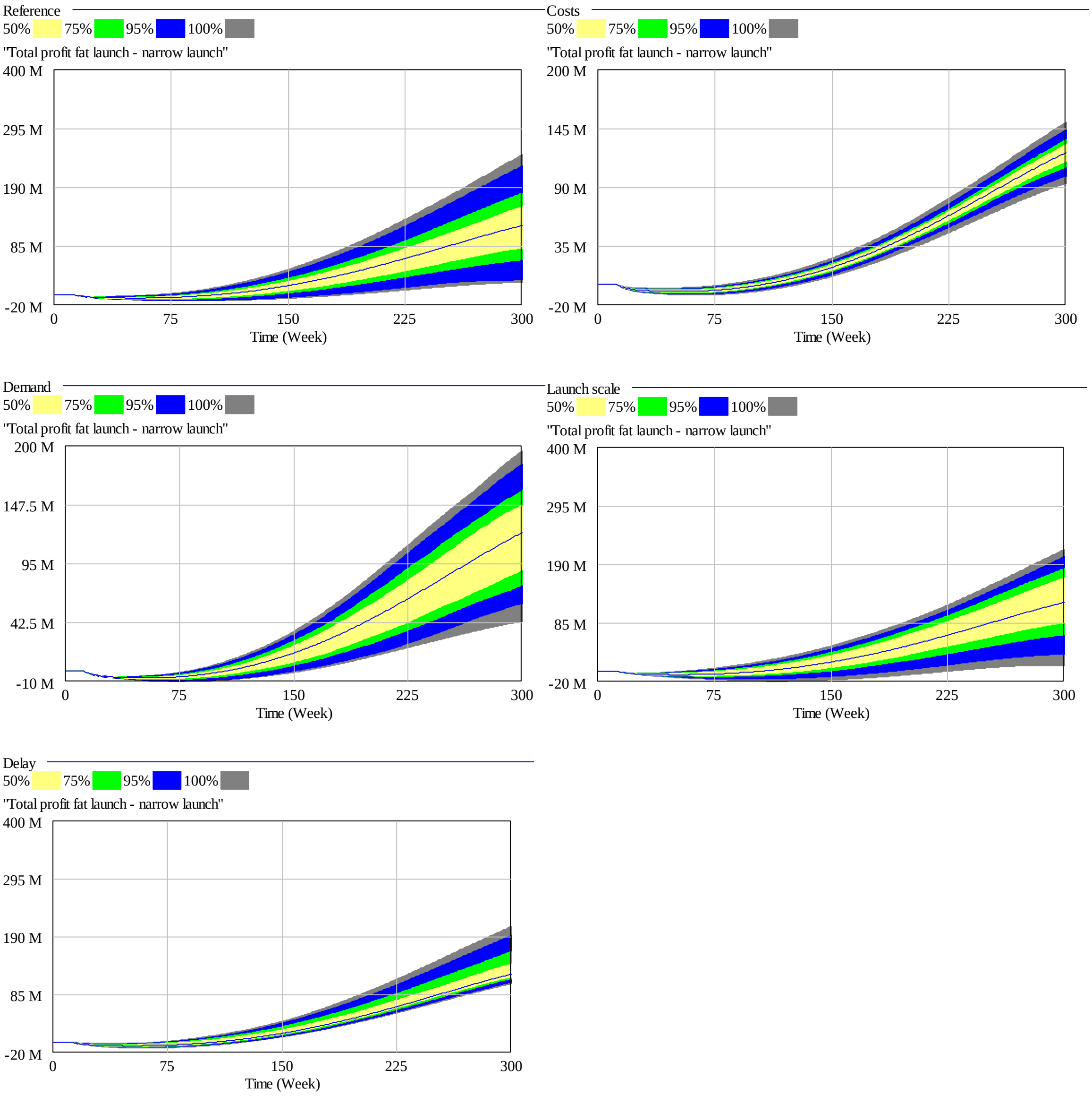
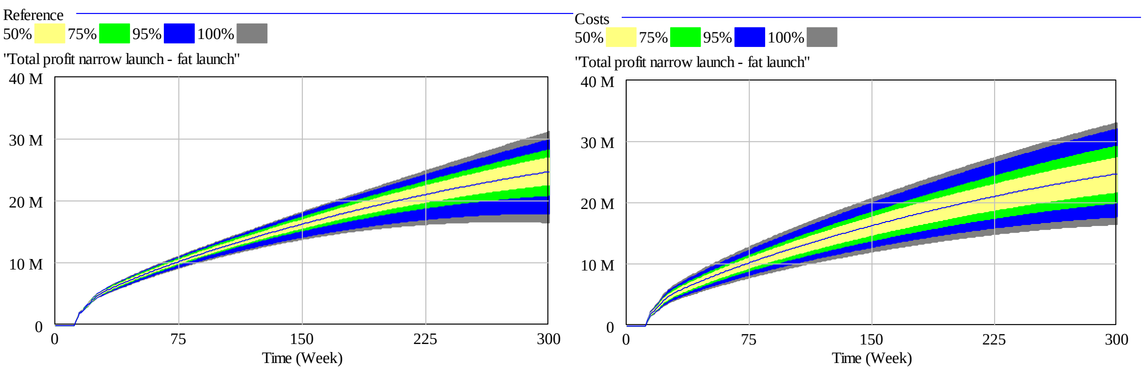


Fig. 1. Sensitivity analysis: static launch strategies under high market responsiveness



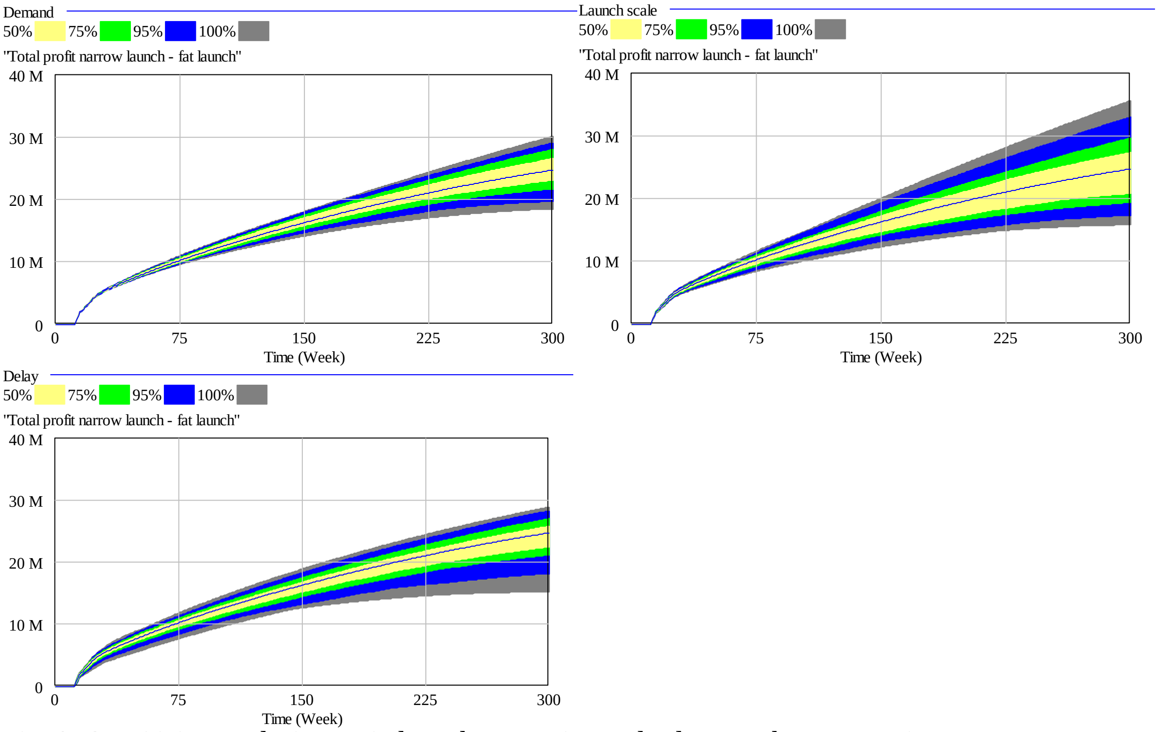
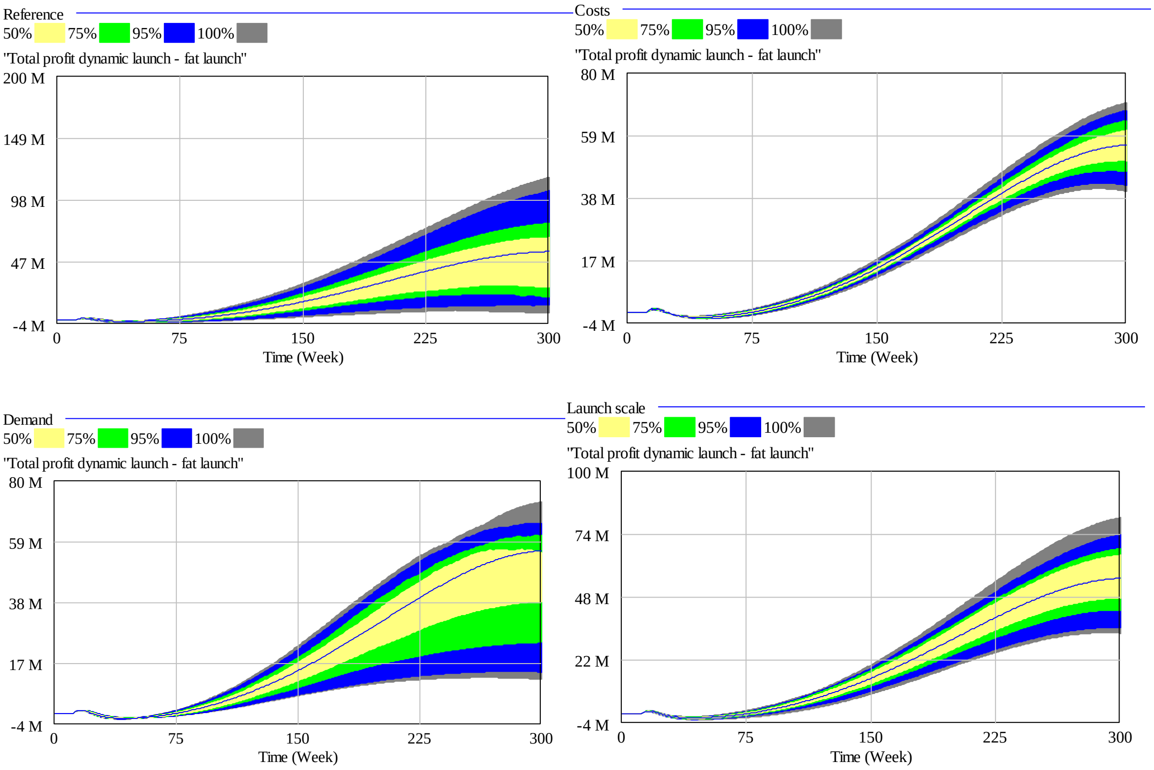


Fig. 2. Sensitivity analysis: static launch strategies under low market responsiveness



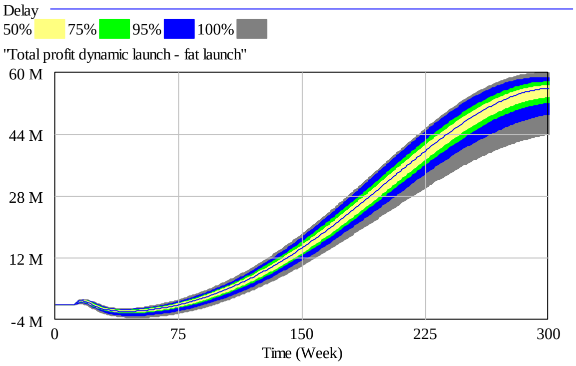


Fig. 3. Sensitivity analysis: dynamic launch strategies under high market responsiveness

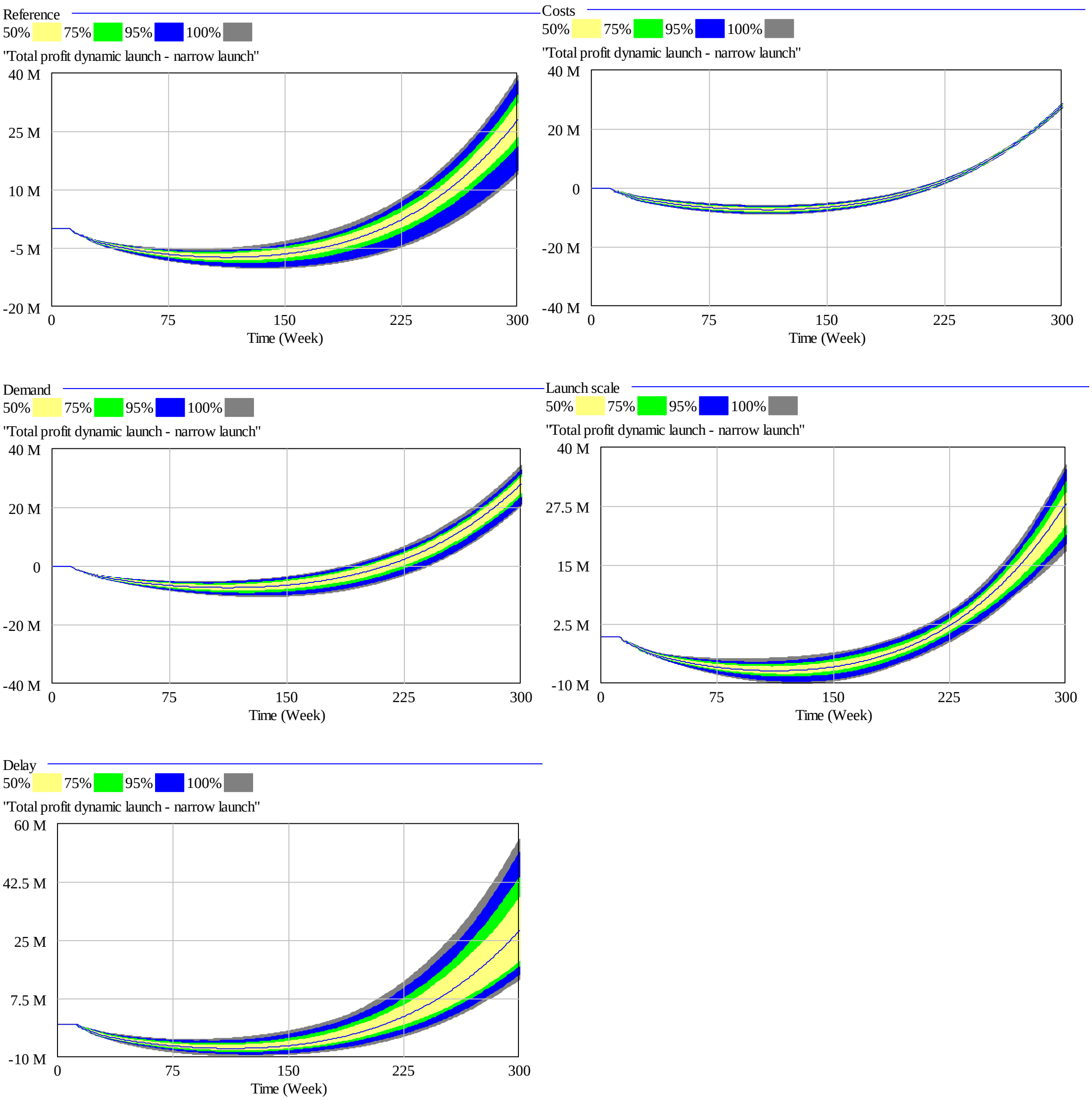


Fig. 4. Sensitivity analysis: dynamic launch strategies under low market responsiveness