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Alternative Supply Chain Production-Sales Policies for New Product Diffusion: An Agent-Based Modeling and Simulation Approach

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Abstract

Applying Agent-Based Modeling and Simulation (ABMS) methodology, this paper analyzes the impact of alternative production-sales policies on the diffusion of a new product and the generated NPV of profit. The key features of the ABMS model, that captures the marketplace as a complex adaptive system, are: (i) supply chain capacity is constrained; (ii) consumers' new product adoption decisions are influenced by marketing activities as well as positive and negative word of mouth (WOM) between consumers; (iii) interactions among consumers taking place in the context of their social network are captured at the individual level; and (iv) the new product adoption process is adaptive. Conducting over 1 million simulation experiments, we determined the "best" production-sales policies under various parameter combinations based on the NPV of profit generated over the diffusion process. The key findings are as follows: (1) on average, the build-up policy with delayed marketing is the preferred policy in the case of only positive WOM as well as the case of positive and negative WOM. This policy provides the highest expected NPV of profit on average and it also performs very smoothly with respect to changes in build-up periods. (2) It is critical to consider the significant impact of negative word-of-mouth on the outcomes of alternative production-sales policies. Neglecting the effect of negative word-of-mouth can lead to poor policy recommendations, incorrect conclusions concerning the impact of operational parameters on the policy choice, and suboptimal choice of build-up periods.

Keywords: *Supply chain management, Agent-based simulation, New product diffusion, Word of mouth*

1. Introduction

Decisions concerning effective supply chain production, sales and entry policies to introduce a new product to the marketplace are critical and often difficult to make, requiring an in-depth understanding of the underlying diffusion processes. Consequences of these supply chain decisions and policies impact the financial livelihood of a company. The significance of production, sales, and diffusion policies is indicated by the fact that average sales and profits from new product introductions reach 32% of overall sales and 31% of overall profits of a firm (Griffin, 1997; Hauser, Tellis, & Griffin, 2006). Capacity decisions are especially difficult for innovative products with a short lifecycle (Kamath and Roy 2007).

The problems that arise when supply and demand processes are not properly understood are highlighted by the cases of Tamagotchi and Playstation 3. Tamagotchi, the first virtual pet, was introduced by Bandai in 1996. Due to extreme word-of-mouth (WOM), demand increased very quickly and exceeded expectations and insufficient capacity led to lost sales; when Bandai finally extended its capacity, demand declined (Higuchi & Troutt, 2004). While initial sales of Sony's Playstation 2 (PS2) were more than ten times that of the original PS's introduction five years earlier (New York Times, 2000), the launch of Playstation 3 (PS3) was not successful and resulted in \$1.8B annual loss in its game division and layoff of 3% of its workers (Los Angeles Times, 2007).

The key objectives of this study are to advance the current literature on the interaction between the diffusion processes of new products and supply chain production-sales decisions; to compare the performance characteristics of three production-sales policies, myopic, build-up, and build-up with delayed product roll-out, under restricted supply with positive and/or negative WOM based on the net present value of profit generated; and to provide managerial recommendations concerning the best production-sales policy and the optimal number of build-up periods. To the best of our knowledge, there is no evidence in the published literature focusing on the hybridization of new product diffusion and supply chain policies, where supply chain capacity is limited; negative WOM is present; and consumers' interactions are conducted via a social network.

The study achieves these objectives by developing an agent-based simulation model (ABMS) that considers the new product diffusion process as a complex adaptive system where:

(a) individual consumer decision is subjected to nonlinear interactions and positive and negative WOM in the consumer social network; (b) the diffusion process is an adaptive system where the current status of adoption throughout the social network is influenced by the adoption decisions made in previous diffusion periods, the marketing activities, WOM, production capacity, and carrying inventory; and (c) both consumer interactions and the diffusion process are considered dynamic throughout the entire diffusion period. The remainder of this paper is organized as follows. Section 2 provides a literature review. In section 3, we present the ABMS methodology; introduce the model components; develop an ABMS model; sketch an ABMS algorithmic design; and present our computational experimental design. In section 4, we discuss the computational results and managerial implications. Finally, in section 5 we present summary, conclusions, and potential extensions of this study.

2. Literature Review

Focusing on the demand side and ignoring the issues relevant to supply, the diffusion process of new products has traditionally been analyzed in the marketing literature. Diffusion models for single products as well as competitive products have been proposed (Yan & Ma, 2011). Marketing and pricing strategies for new innovations were explored using optimal control theory (Kamrad, et al., 2005). Empirical research determined the effect of interaction on product diffusion and adoption (Emmanouilides & Davies, 2007) and the effect of advertising on subscriber service adoption (Mesak, et al., 2011).

The majority of innovation diffusion models are based on the classical Bass model (Bass, 1969). Bass depicts the new product diffusion process using two parameters: marketing activity and WOM among consumers (Mahajan, Muller, & Bass, 1990). Generally, Bass-type models only consider the effect of positive WOM and assume unrestricted availability of supply. Additionally, the outcomes of the diffusion process generated by these models are at the aggregate market level (Bass, 1969, 2004). Capturing market effect, positive WOM, unrestricted product supply and aggregate diffusion outcome allows modelers to model the new product diffusion process in closed-formulation; and hence allows them to produce exact model solutions.

The importance of analyzing diffusion processes while considering supply restrictions was first discovered in the marketing science literature by Simon and Sebastian (1987), who analyzed the diffusion of telephones in Germany. Based on insights by Simon and Sebastian (1987), Jain *et al.* (1991) developed an extended Bass model that includes supply constraints. They used the resulting model to forecast the demand of new telephones in Israel. Swami and Khairnar (2006) developed a sales prediction model by extending the Bass model to include supply constraints as well as an expiration date. They explicitly include the scarcity effect that highlights that opportunities are more valuable when they are scarcer. Stonebraker and Keefer (2009) suggest a methodology based on decision analysis to calculate potential demand for supply constrained products.

While marketing literature focuses on developing supply restricted diffusion models to improve sales forecasts, researchers in the operations literature concentrated on developing supply-restricted diffusion models to enhance quality of capacity, production and sales decisions. In the operations literature, Ho *et al.* (2002) relax the assumption that demand is given and independent of capacity decisions. They developed an extended Bass model that includes capacity constraints. Their model finds the optimal production and sales plans that maximize profit during the new product's life-cycle, spanning from one to two years. They determine that delaying sales is never a beneficial policy. Kumar and Swaminathan (2003), however, who also extend the Bass model to include supply constraints, show that delaying sales can be a beneficial policy under certain conditions. They show that the build-up policy is robust and very close to optimal on average, and under certain scenarios the myopic policy may deviate far from optimal. Xiaoming et al. (2011) developed a supply restricted diffusion model that also includes negative WOM from consumers who do not receive the product. Although the previous models introduced in the literature offer valuable contributions in studying the dynamics of the supply or demand side independently or simultaneously, they had their own limitations. First, these models produce new product diffusion results at the aggregate level, ignoring the impact of individual consumers on the diffusion process. Second, although critical, they do not consider the effect of negative word-of-mouth (WOM) caused by consumers who buy the product but are not satisfied with the quality of the product. Third, previous model developments ignore the consumers social networks within which individual consumers interact.

More recently, studies have highlighted the importance of the relationship between individual consumer behavior and aggregate market outcomes (Bass, 2004; Garcia, 2005; Guenther, et al., 2010; Hauser, et al., 2006). These studies have shown that individual consumer interactions, positive and negative, provide important insights about aggregate diffusion (Garber, et al., 2004; Goldenberg, et al., 2007; Goldenberg, Libai, & Muller, 2002). They showed that negative WOM not only impacts individual-level adoption, but it can also have a negative impact on diffusion outcomes. Usually, only a small percentage of consumers report their complaints to the firm; therefore, marketers can easily underestimate the presence of negative WOM in the marketplace and its potential impact on new product diffusion. The most common sources of negative WOM are known to be dissatisfied adopters or product rejecters. Regardless of the source, due to the non-linear adaptive nature of negative WOM circulation, even a small percentage of dissatisfied consumers can significantly reduce firms' revenues. While Goldenberg et al. (2007) highlighted the importance of negative WOM in the context of diffusion processes without supply restrictions, models that studied optimal capacity and sales decisions in the context of supply-restricted diffusion processes did not consider the effect of negative WOM from dissatisfied consumers, at consumer or aggregate levels. Table 1 summarizes previous literature.

	Diffusion Without Capacity Constraints	**Diffusion With Supply Constraints**
Only Positive WOM	e.g. Bass (1969); Mahajan and Muller (1998); Goldenberg et al. (2002); Garberetal (2004); Vanden Bulte and Joshi (2007); Iyengar et al. (2008)	Simon and Sebastian (1987); Jan et al. (1991); Swami and Kairnar (2001); Kumar and Swaminathan (2003); Ho, Savin, and Terwiesch (2008)
Positive and Negative WOM	Goldenberg et al. (2007)	(Xiaoming, et al., 2011)

Table 1. Literature Review

3. ABMS Model Development and Computational Experimental Design

While manufacturing and logistics operations can be characterized as complex (Nilsson and Darley 2006), there are only few applications of complex systems methods in the area of production and operations management (Baldwin, Allen, & Ridgway, 2010). A complex adaptive system (CAS) is composed of interacting components and adapts to its changing environment. In studying complex adaptive systems, simple interactions among components and its environment might result in unpredicted complex patterns, referred to as emergence phenomena. Modeling embedded complexities, including system dynamism, adaption, and nonlinear interactions, approaches the limits of traditional modeling methods (Garcia, 2005; North & Macal, 2007). Agent-based models provide valuable insights concerning tactical and operational decisions in complex systems (Nilsson & Darley, 2006).

An agent-based model is built on the interactions between decision-makers as opposed to an equation-based model that is constructed based on a set of equations that reflects observables (Parunak, Savit, & Riolo, 1998). Relying on extensive computational experiments, Rahmandad and Sterman (2008) conclude that deterministic models, differential equation models, and agent-based models differ for several metrics including diffusion speed and peak load and that these models respond differently to intervention policies, even when the base cases behave similarly. Successful applications of ABMS include models to simulate the process of technological innovation (Ma & Nakamori, 2004), technological market structure evolution in electricity markets (Bunn & Oliviera, 2007), production strategies in the lumber industry (Yáñez, et al., 2009), and distribution strategies of a novel biomass-fuel (Guenther, et al., 2010).

The marketplace under study resembles a complex adaptive system that is driven by socially networked consumer interactions and, hence, can be best studied using an ABMS (Miller & Page, 2007; North & Macal, 2007). ABMS allows us to capture: (a) consumers as agents with three essential attributes: autonomy, interactivity, and bounded rationality; (b) dynamic social network interactions among consumers; (c) the effect of marketing activities on consumers; (d) positive and negative WOM between consumers; and (e) adoption status of individual consumers as well as aggregate diffusion at the market level throughout the new product diffusion process. As in Kumar and Swaminathan (2003), we assume that the marketplace consists of a single firm that sells a new "generic "consumer product, price does not impact a consumer's buying decision, and consumers are engaged in a one-time purchase decision.

In this section, we present discussions about the following topics: (3.1) consumers' social network attributes and adoption decision (3.2) alternative production-sales policies to study; (3.3) NPV as the performance measurement applied for comparative analysis among alternative production-sales policies; (3.4) ABMS algorithm developed and implemented for this study; and (3.5) the ABMS computational experimental design.

3.1 Consumer Social Network and Adoption Decision

Interactions between consumers emerge in the context of their social networks. Social networks provide the setting for individuals to interact and exchange information (Barabasi, 2002; Watts & Strogatz, 1998). The structure of consumer social networks is not known with certainty (Alderson, 2008; Watts & Dodds, 2007). A few recent studies that attempted to map large scale social networks resulted in different network structures (Bampo, et al., 2008; Goldenberg, et al., 2009). In the absence of empirical details about social network structure, we assume a random network structure as a “null” hypothesis (Alderson, 2008).

A recent experiment found that the average number of consumers’ social ties is 25 (Goldenberg, et al., 2007). This number is in line with that found in a panel of 250,000 teenagers by Tremor of P&G (McCarthy, 2007). Therefore, we assume that the average number of social ties is 25. Similar to earlier studies (e.g., Goldenberg, et al., 2007; Kumar & Swaminathan, 2003), we model a market of 3,000 consumers. To discover whether a larger size market may impact the simulation results, we repeated experimental designs on larger networks. The analysis showed no significant differences in the simulation results; hence, we chose a random network structure linking 3,000 consumers for all designed experiments. We terminated an experiment when 95% of 3,000 potential consumers made adoption decisions.

We now describe the decision-making process applied by socially-networked consumers regarding product adoption or rejection at each period. We describe consumers’ decision-making process in the cases, where both positive and negative WOM are present. For the cases with only positive WOM product rejecters and dissatisfied adopters,were removed from the model.

As depicted in Figure 1, at the beginning of each period consumers are divided into three major groups: undecided consumers, adopters, and rejecters. The adopters are grouped into two sub-groups: adopters with met demand and adopters with unmet demand. In addition, adopters with met demand can be further categorized into satisfied and dissatisfied consumers. Adopters with unmet demand include : adopters who are waiting to receive the product and lost consumers. While consumers in the satisfied-adopters group engage in positive WOM, dissatisfied-adopters, and lost-consumers communicate negative WOM. Undecided and waiting consumers engage neither in negative nor positive WOM.

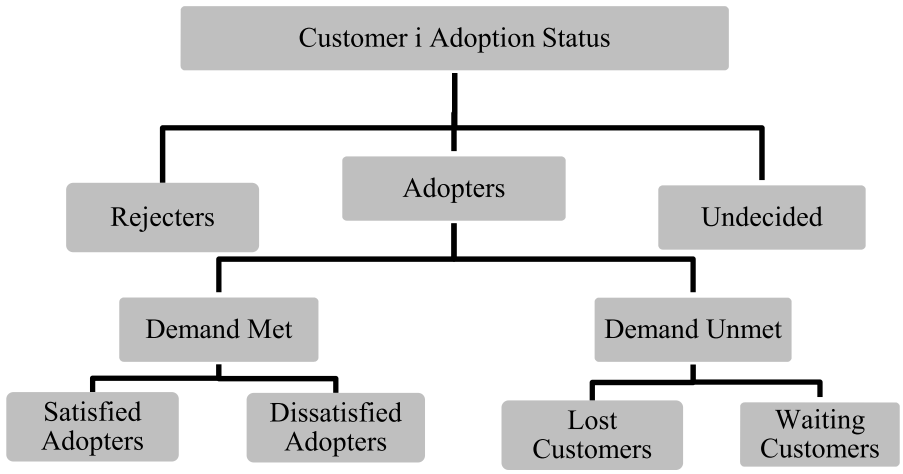

Figure 1. Consumer New Product Adoption Status

As in Goldenberg (2007), consumers' decisions are influenced by direct positive and negative WOM and marketing efforts. We only consider WOM between agents who have direct social ties. Figure 2 shows that a potential consumer, at any diffusion period, might have direct social links to the members of six groups of consumers: satisfied adopters, dissatisfied adopters, rejecters, lost, waiting, and undecided. In making an adoption decision, through direct social ties the potential consumer receives positive WOM from satisfied adopters and negative WOM from dissatisfied adopter, lost, and rejecter groups. Based on the aggregate levels of positive and negative WOM, the consumer make a decision as to adopt, reject, or stay undecided. The mathematical model for potential consumer decision making is presented at the end of this section.

The strength of the impact of WOM is captured by the coefficient of imitation, q, and the effect of marketing effort is captured by the coefficient of innovation, p. When defining ranges and values for parameter p and q at the individual level, we relied on two groups of studies: (1) Empirical studies validating parameter values at the aggregate level; and (2) Studies that suggest methods for calculating individual-level parameter values q_j based on aggregate level parameters (Goldenberg, et al., 2007; Goldenberg, et al., 2002; Toubia, Goldenberg, & Garcia, 2008). Therefore, the individual-level values used for parameters p and q generate aggregate results that are comparable to those of the aggregate level models. To calculate the individual-level parameters, we chose the value of aggregate-level parameters q = 0.4 and p = 0.03. The selected

p and q represent average values considered for a typical product (Jiang, Bass, & Bass, 2006; Sultan, Farley, & Lehmann, 1990). We then transformed the values of aggregate-level parameter q to individual-level parameter q_j by dividing it by the number of links of each individual (i.e., 25). The value of parameter p will be the same for both individual-level and aggregate-level models (Goldenberg, et al., 2002; Toubia, et al., 2008).

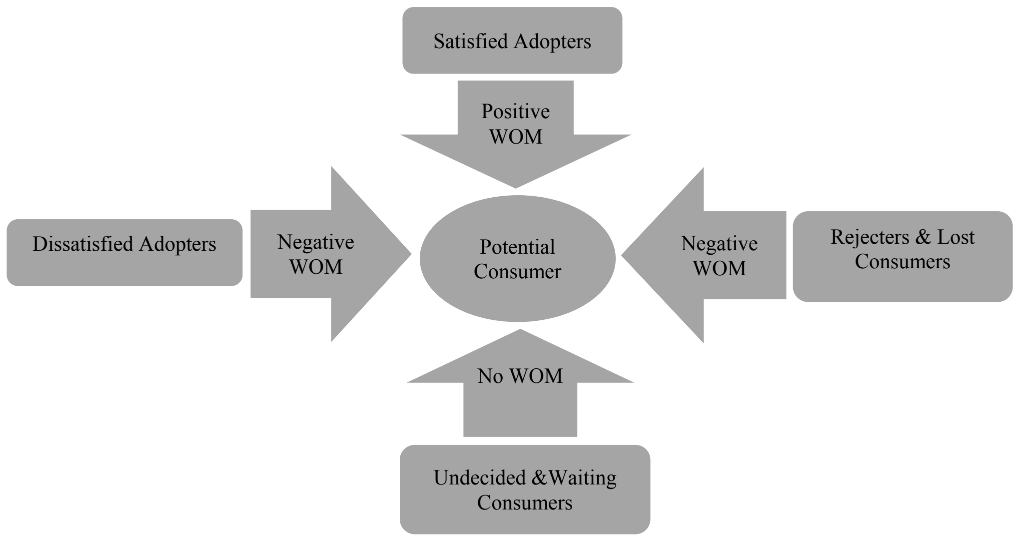

Figure 2. Word-of-Mouth through Direct Social Ties to Members of Other Consumer Groups

Influenced by WOM and marketing efforts, potential consumers decide to adopt the product, reject it, or stay undecided. While positive WOM communicated with the undecided consumer through his/her social ties and marketing effort encourage undecided consumers to adopt the new product, negative WOM discourages potential adopters from adopting. The impact of negative WOM on an undecided consumer is calculated by identifying the number of rejecters, dissatisfied adopters, or lost consumers among her/his social ties. $L(i)^{+}$ is the index set of consumers with whom consumer i has social ties and who are sources of positive WOM (satisfied adopters). $L(i)^{-}$ is the index set of consumers with whom consumer i has social ties and who are sources of negative WOM.

Generally, the marketing literature suggests that negative WOM has a greater impact on potential consumers' adoption decisions than positive WOM (e.g., Arndt, 1967; Harrison-Walker, 2001) due to two main reasons: (1) People assign more weight to negative WOM than to positive WOM (Hart, Heskett, & Sasser, 1990; Mizerski, 1982) (2) A dissatisfied consumer talks to more people than a satisfied consumer (Anderson, 1998; TARP, 1982, 1986). In line with earlier studies and accepted industry practices (Goldenberg, et al., 2007; Hart, et al., 1990; TARP, 1982, 1986), he relative power of negative WOM to positive WOM is fixed at 2.

To determine the adoption status of an undecided consumer *i* in period *tnow*, first we determine the probability of consumer *i* to be influenced by either external advertisement or by internal positive WOM, $p^+_{(i,tnow)}$, received from satisfied consumers having direct social network links with consumer *i* as follows:

$$p^+_{(i,tnow)} \leftarrow 1 - (1-p)\prod_j (1-q_j), \text{ where } j \in L(i)^+ \qquad [1]$$

In equation [1], $(1-p)$ indicates the probability that consumer *i* is not influenced by the positive impact of advertisement. In addition, the probability of consumer *i* not receiving positive WOM from any of the satisfied adopter *j* with direct social link is $(1-q_j)$. The product of these two terms indicate the probability of consumer *i* not receiving any positive influence from neither advertisement or satisfied consumers with direct social links. Subtracting the product of the two terms from 1 indicates the probability of consumer *i* receiving positive influence from advertisement or satisfied adopters with direct social links.

Next, we determine the probability of negative WOM $p^-_{(i,tnow)}$, received by consumer *i* from dissatisfied adopters, product rejecters, and lost consumers as follows:

$$p^-_{(i,tnow)} \leftarrow 1 - \prod_j (1 - \mathrm{M} * q_j), \text{ where } j \in \mathrm{L}(i)^- \qquad [2]$$

Assuming that the impact of negative WOM is M times the positive WOM, in equation [2] the probability of consumer *i* not receiving any negative WOM at diffusion period *tnow* is the product of $(1 - \mathrm{M} * q_j)$ for all dissatisfied consumers *j* with direct social links. Subtracting this product from 1, results in the probability of consumer *i* receiving negative WOM.

To calculate the transition probability, we need to recognize that a potential consumer *i* at period *tnow* may be exposed to positive influence, negative influence, both positive and negative or neither. Hence, the probability of being exposed to only positive WOM is given by (1 - $p^-_{(i,tnow)}$) $p^+_{(i,tnow)}$, also for only negative WOM (1 - $p^+_{(i,tnow)}$) $p^-_{(i,tnow)}$. In addition, the probability of being influenced by both positive and negative WOM is measured by $p^+_{(i,tnow)}$ $p^-_{(i,tnow)}$. We allow a proportion of α_i of the consumers that are influenced by both negative and positive WOM to adopt the product, and (1 - α_i) to reject. The normalization factor, α_i, indicating the ratio of positive WOM over the total WOM influence received by consumer *i*, both positive and negative is calculated by:

$$\alpha_i = \frac{p^{+}_{(i,tnow)}}{\left(p^{+}_{(i,tnow)} + p^{-}_{(i,tnow)}\right)} \qquad [3]$$

Given this normalization factor, the probabilities of product adoption, $p^{adopt}_{(i,tnow)}$, rejection, $p^{reject}_{(i,tnow)}$, or wait-to-decide, $p^{wait}_{(i,tnow)}$, for an undecided consumer *i* at period *tnow* are determined by:

$$p^{adopt}_{(i,tnow)} \leftarrow (1 - p^{-}_{(i,tnow)})p^{+}_{(i,tnow)} + \alpha i p^{+}_{(i,tnow)}p^{-}_{(i,tnow)}, \qquad [4]$$

$$p^{reject}_{(i,tnow)} \leftarrow (1 - p^{+}_{(i,tnow)})p^{-}_{(i,tnow)} + (1 - \alpha i)p^{+}_{(i,tnow)}p^{-}_{(i,tnow)}, \qquad [5]$$

$$p^{undecided}_{(i,tnow)} \leftarrow (1 - p^{+}_{(i,tnow)})(1 - p^{-}_{(i,tnow)}). \qquad [6]$$

Equations [4], [5], and [6] would add up to 1. Given *d* as the percentage of dissatisfied consumers, consumer *i* becomes a satisfied adopter with probability of$dp^{adopt}_{(i,tnow)}$, a dissatisfied adopter with probability of $(1 - d)\ p^{adopt}_{(i,tnow)}$, and a rejecter with probability of $p^{reject}_{(i,tnow)}$. Consumer *i* in period *tnow* might stay undecided with probability of $p^{undecided}_{(i,tnow)}$.

3.2 Production-Sales Policies to Study

In this study, we compare performance characteristics of three alternative production-sales policies: myopic, build-up, and build-up with delayed roll-out (build-up 2). As Kumar and Swaminathan (2003) point out, while computing optimal production-sales plans explicitly is quite difficult, the myopic and build-up policies have simple, intuitive structures and could be used as heuristics to closely estimate "optimal" plans. We consider three alternatives using ABMS, rather than using a closed-formulation. Table 2 shows the characteristics of the three production-sales policies with respect to the time period when production, marketing activities and sales start.

Policy	Start of Production	Start of Marketing Activities	Start of Sales
Myopic	Period 1	Period 1	Period 1
Build-up	Period 1	Period 1	Period t>1
Build-up 2	Period 1	Period t>1	Period t>1

Table 2. Policy Comparisons

In the myopic policy, the company begins producing, promoting and selling the product in period 1. In each period it sells as much as possible. If a firm applies the build-up policy, production and promotion begins simultaneously in period 1. Marketing activities during the build-up period will generate some demand, but the product is not available for sales. Hence, interested consumers must wait until the build-up period is completed, or withdraw.. Thus, during the build-up period, no revenue is realized, but the variable, inventory holding, and consumer waiting costs would occur, resulting in negative NPV profit. After the build-up, the company sells as much as possible. For the build-up policy with delayed roll-out (build-up 2), the company begins producing in period 1, but marketing and product sales start after the initial build-up period is passed. In build-up 2, no demand is generated during the build-up period and so no consumers are lost. An example of this is the delayed roll-out of Playstation 2 by Sony (Kumar & Swaminathan, 2003). The ABMS parameters for the production-sales policies are selected as follows. Assuming that the overall diffusion period is between one to two years (with each period lasting two to four weeks), the number of periods is estimated to be 30. Accordingly, the production capacity per period is set to 100. Regardless of the policy , production begins in period 1. The decision concerning production quantity is made based on expected demand. As long as the percentage of consumers who made adoption decisions is below 84% of the market potential (3,000 consumers), the production quantity is equal to the production capacity. After this threshold is reached, the number produced is set to the demand in the previous period. The choice of 84% was made due to the fact that the last 16% of the market potential who adopt a new product, referred to as laggards, are slow in adopting (Rogers, 2003). Utilization of the maximum capacity during this period might introduce carrying inventory and, hence, increase total costs. In addition to the aforementioned parameters, performance characteristics of build-up 1 and build-up 2 are impacted by the number of build-up periods. The range of build-up periods in the designed simulation experiments is between 1 and 12.

3.3 NPV Calculation

Performance characteristics of different production-sales policies are compared based on the NPV of the overall profit they generate throughout the diffusion period. Each policy is initiated with a negative net present value, reflecting fixed cost. To determine net profit for a policy in each diffusion period, the total of relevant costs including variable costs, carrying inventory costs, and consumer waiting costs is subtracted from the current period gross revenue (unit price times units sold). Next, using a discount rate, the NPV of the profit generated for the period is determined. Finally, the NPV of the period under consideration is added to the total net present value.

3.4 The ABMS Algorithm in Brief

In this sub-section, we present the ABMS simulation algorithm for the myopic policy. The supplement details an ABMS pseudo-algorithm developed and implemented for this study. The ABMS algorithm for all alternatives is described in the supplement.

Regardless of the policy under consideration, at the beginning of each period, the available supply includes the carrying inventory from the previous period and the current production. Before continuing the process, we allocate the current supply to meet the demand of waiting consumers. If possible, we meet the demand of all waiting consumers. Otherwise, the remaining waiting consumers with unmet demand have may keep waiting or withdraw. Any time a waiting consumer leaves, potential revenue is lost. After the waiting consumers are resolved, we might have exhausted product supply. If not, the diffusion process continues with some positive level of carrying inventory. As we continue the process, we apply equations [1] through [6] to determine the adoption status of each undecided consumer. If an individual consumer decides to adopt the product, then depending on the availability of supply, his/her demand could be met or the consumer must decide whether to join the waiting consumers group or completely withdraw.

3.5 The ABMS Computational Experimental Design

Given this set of issues of interest – type of WOM and build-up decisions – a total of six simulation scenario models were developed for the computational study. Figure 3 shows the classification of the six different simulation scenario models.

The selected parameter values, ranges, and adoption sources used in experiments with the six ABMS models are summarized in Table 3. The purpose of selecting parameters from previous papers was to have a basis for comparison of the results produced by our ABMS modelling effort. The flexibility embedded in the current ABMS models readily allows consideration of other parameter sets. These parameters are organized in four subsets: consumer social network; new product diffusion; production-sales policies; and simulation termination criteria.

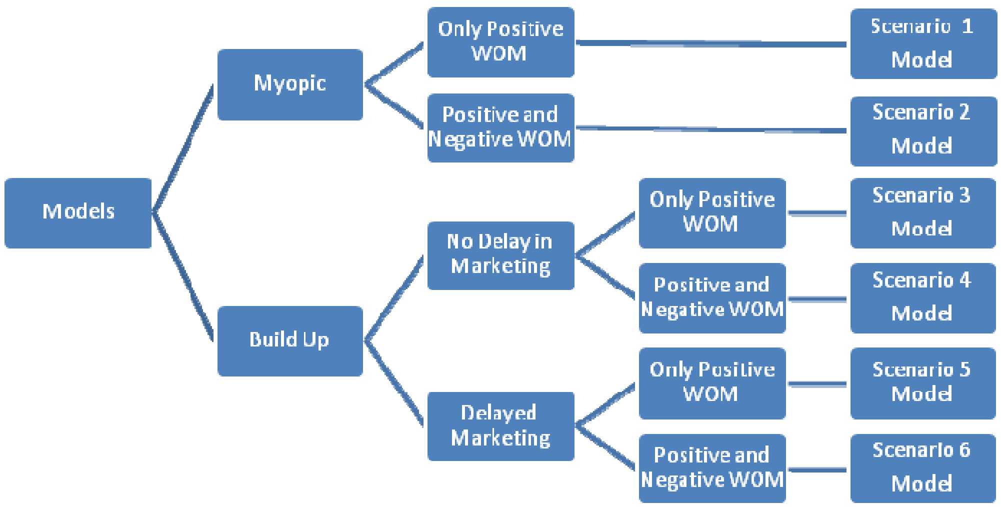

Figure 3. The Six ABMS Simulation Scenarios (Models)

Given a simulation model in Figure 3 and a selected parameter combination, we complete the simulation experiment as follows. First, we generate five random social networks, each including 3,000 consumers. Using each of the five networks, we replicate simulation of the new product diffusion process 10 times, each with a new random number stream. In total, for each parameter combination applied to a given simulation scenario model, we generate 50 sets of simulation results. The number of replications per experimental cell was determined based on a steady-state analysis, which indicated that the minimum number of replications necessary for stability is 50.

While models 1 and 2 each include 432 parameter combinations, models 3 to 6 each include 5,184 parameter combinations. Considering all six simulation scenario models and parametric combinations, the computational experiments produced results for a total of 1,080,000 experiments. For each scenario, a simulation algorithm was developed and implemented. The algorithms were developed on a standard Dell desktop (Xeon, CPU 3.2 GHz, and 2.00 GB of RAM), Microsoft Windows XP Professional 2002 operating system, in Compaq Visual Fortran environment. All computational experiments were conducted in the same environment.

ABMS Simulation Model Parameters		
Parameters	**Parameter Value or Range**	**Selection Sources**
Market size	3,000	Kumar and Swaminathan (2003)
Average number of social ties per consumer	25	Goldenberg *et al.* (2007)
Coefficient of innovation	0.03	Sultan *et al.* (1990)
Coefficient of imitation	0.40	Sultan *et al.* (1990)
Percentage of dissatisfied adopters	5 %	Goldenberg *et al.* (2007)
Relative power of negative WOM to positive WOM (*M*)	2	Goldenberg *et al.* (2007); Hart *et al.* (1990); TARP (1982); TARP (1986)
Supply chain capacity per period	100	Kumar and Swaminathan (2003)
Unit capacity fixed cost	10	Above
Unit variable cost	1	Above
Unit backlogging cost per period	0.01, 0.005, and 0.001.	Above
Unit selling price	1.1, 1.2 and 1.3	Above
Unit inventory holding cost	0.01, 0.005 and 0.001	Above
Discount rates	0.01, 0.005, 0.003 and 0	Above
Percentage of backlogged demand	0, 0.5, 0.8, and 1	Above
Build-up periods	0-12	Above
Percentage of market adoption at which supply chain capacity is adjusted to previous period demand	84 %	Rogers (2003)
Percentage of consumers who made adoption decision at which simulation is terminated	95 %	Goldenberg *et al.* (2007); Rogers (2003)

Table 3. Parameter Choices for ABMS Computational Experiments

4. Analyses of Simulation Results

In this section, we present the results. Based on the experimental design, we study the three production-sales policies described in the previous sections. The performance characteristics of the three policies are compared based on the net present value of profit generated over the diffusion process. In a complex system such as the one modelled, it is vital to make sure that the simulation performs as anticipated. To ensure this, we evaluated a set of pilot runs in detail. Outcomes such as profit were evaluated with respect to changes in each of the input parameters. In addition, analyzing diffusion processes with only positive WOM allowed us to compare our results to those in Kumar and Swaminathan (2003).

4.1 Production-Sales Policy Comparison for Best Cases

In this section, we compare the NPV generated by the three policies assuming that the decision-maker can choose the optimal number of build-up periods. In Section 4.3, we analyze how sensitive NPV of profit is with respect to changes in build-up periods. We found the best NPV for each case / parameter combination by comparing the average NPV of the different build-up periods and picking the build-up period that generates the highest NPV of profit. This procedure provided us with 432 best NPVs for each one of the 6 cases. In each comparison, we evaluated the relative difference between these outcomes. "Total Premium" indicates the overall performance of a model summed over all 432 parameter combinations, that is:

$$TotalPremium = \left(\sum Scenario1\ NPV - \sum Scenario2\ NPV\right) / \sum |Scenario2\ NPV|$$

	Positive WOM			**Positive and Negative WOM**		
Scenario 1	Build-up 1	Build-up 2	Build-up 2	Build-up 1	Build-up 2	Build-up 2
Scenario 2	Myopic	Myopic	Build–up 1	Myopic	Myopic	Build–up 1
Total Premium	7 %	23 %	15 %	- 2 %	79 %	82 %
Total premium increases if:						
Inventory Holding Cost	Decreases	Decreases	Decreases	Decreases	Decreases	Decreases
Discount Rate	Decreases	Decreases	Decreases	Decreases	Decreases	Decreases
Waiting Cost	Increases	Increases	Increases	Decreases	Increases	Increases
Backlogged Demand	Pattern not Consistent	Pattern not Consistent	Pattern not Consistent	Increases	Decreases	Decreases

Table 4. Total Premium

We first compare the 3 policies in the presence of only positive WOM . This will provide us with a base case against which we can compare the results of the diffusion process influenced by positive and negative WOM. Table 4 indicates that in the case with only positive WOM, build-up policy 1 outperforms the myopic policy by 7% overall. Since build-up policy 1 leads to longer build-up periods, more inventory, delayed sales, and fewer waiting consumers, the average premium of build-up policy 1 compared to the myopic policy increases when the inventory holding cost decreases, the discount rate decreases, and waiting cost increases. These insights are in line with results found by Kumar and Swaminathan (2003). Furthermore, Table 4 indicates that build-up 2 outperformed build-up 1 by 15 % overall in the case of only positive

WOM. The average premium of build-up 2 increases when the inventory holding cost decreases, the discount rate decreases, and the waiting cost increases, indicating that build-up 2 leads on average to delayed sales, more inventory, and fewer waiting consumers than build-up 1.

The trends in Table 4 are worth noting. Not surprisingly, total premiums of build-up 1 decrease as holding costs increase. Since any build-up policy will tend to hold inventory longer than a myopic policy, the build-up policy becomes more attractive as holding costs decrease. In a similar vein, build-up 2 gains in preference on build-up 1 as holding costs decrease: the benefits of early marketing with respect to inventory are lessened.

A similar pattern holds for the discount rate. Across the board, we note an increase in the total premiums, as the discount rate decreases. Models that tend to hold more inventory (build-up vs. myopic) or market later (build-up 2 vs. build-up 1) benefit greatly when penalized less for those holdings. This highlights the importance of inventory management.

In the case of only positive WOM, total premiums increase with an increase in waiting costs, for build-up 1 vs. myopic. This pattern suggests that the availability of inventory provided by an early build-up is rewarded significantly as it will reduce the number of those who have to wait. Interestingly, total premiums also increase, for build-up 2 vs. build-up 1. This result suggests that build-up 2 leads to fewer waiting customers, since marketing is delayed.

The impact of a change in waiting costs is not quite as clear in the presence of both positive and negative WOM, and it is helpful to consider this in conjunction with backlogged demand. Note that negative WOM is more likely when a customer must wait. As a result, backlogged demand will impact future sales. When comparing build-up 1 to myopic, we actually see a decrease in total premiums when the waiting costs increase. This accentuates the importance of considering negative WOM, as we observe here that decreased waiting costs lead to a more significant advantage for the build-up case. (Note that this is contrary to the PWOM case.) This indicates that the impact of backlogged customers plays a larger role in customer demand (and hence, profits) with the longer wait that is inherent in the myopic case. Due to the delayed marketing that accompanies build-up 2, total premiums still tend to increase vs. build-up 1, as waiting costs increase, as was seen in the PWOM environment. This indicates the value of lagging the marketing effort.

The most complex results occur when studying the impact of backlogged demand. When there is only positive WOM, there is no consistent pattern. So, even though backlogged demand produces a wait, the fact that there are also holding costs and delayed profits leads to too many trade-offs among the elements to identify a strict relationship.

This is not the case, however, in the presence of negative WOM. In this environment, backlogs lead to less satisfied customers. In the comparison of build-up 1 vs. myopic, we see this increased wait enhances the position of building-up prior to product launch. And comparing build-up 2 vs. build-up 1, it is notable that the decreased backlog is more beneficial to build-up 2, again highlighting the value of not proceeding too soon to generate customer interest, particularly, when the backlogs are manageable.

Comparing the cases where we allow only for positive WOM and the cases where we allow for positive and negative WOM, we see that ignoring negative WOM can lead to wrong recommendations. While we see that in the case with only positive WOM, build-up 1 is better than myopic overall as the model by Kumar and Swaminathan (2003) indicates, the myopic policy performs better than build-up 1 overall in the case of positive and negative WOM as the model by Ho et al. (2002) suggests. Furthermore, inconsideration of negative WOM can lead to wrong conclusions concerning the impact of operational parameters on policy choice. An increase in waiting costs increases the total premium of build-up 1 compared to the myopic policy in the case with only positive WOM, while it decreases the total premium in the case with positive and negative WOM.

The previous analysis provided a coarse look at the overall performance of the various scenarios. Next, we consider relative performance, recognizing that there will be variations as parameter combinations change. Mathematically, this Average Premium is calculated as follows:

$$AveragePremium = \frac{\sum((Scenario\#1\ NPV - Scenario\#2\ NPV)\ /|Scenario\#2\ NPV|)}{432}$$

	Positive WOM			**Positive and Negative WOM**		
Scenario 1	Build-up 1	Build-up 2	Build-up 2	Build-up 1	Build-up 2	Build-up 2
Scenario 2	Myopic	Myopic	Build-up 1	Myopic	Myopic	Build-up 1
Total Premium	7%	23%	15%	-2%	79%	82%
Average Premium	6%	25%	16%	-45%	181%	167%
Minimum Premium	-6%	-3%	-2%	-1,810%	-2%	-3%
Maximum Premium	109%	372%	188%	51%	4176%	1018%
Standard Deviation	10%	37%	22%	154%	354%	182%
Scenario 1 Superior	70%	81%	88%	24%	100%	96%
Scenario 1 NPV <0	0%	0%	0%	8%	0%	0%

Table 5. Policy Comparisons

Table 5 indicates that there is a clearer relationship between total and average premiums in the positive WOM cases, than in the cases involving both positive and negative WOM. This would suggest that, when only positive WOM is a factor, both methods tend to perform similarly in all cases; however, when both positive and negative WOM are in play, one model significantly outperforms the other in some cases, and is slightly outperformed by the second model in others.

This fact is evidenced when we look at the Minimum and Maximum lines. For instance, when positive and negative WOM are present, the largest relative gain for the myopic case is 1,810 %, while the largest relative gain for build-up 1 is only 51%. The fact that the average premium is so much smaller than the total premium reveals that such extremes are very common in this instance. For the case of only positive WOM comparing build-up 1 and myopic policy we see that while the minimum is -6% and the maximum is 109%; the average premium and the total premium are fairly close, demonstrating that extreme differences are relatively rare. It is also noteworthy to consider the volatility. When only positive WOM is evident, the standard deviation of the relative performances is 10-37%. Compared to the averages, these are not at all small, suggesting that one model does not completely dominate the other over all 432 scenarios. This unpredictability is even more pronounced when both positive and negative WOM are in play.

The volatility of the system as a function of the parameters is a critical issue. As noted on Table 5, there is quite significant variability in relative performance. "Scenario 1 Superior" indicates the percentage of the 432 combinations in which Scenario 1 outperformed Scenario 2. In the case of PWOM, Build-up 1's NPV exceeds that of the myopic scenario in 70% of the cases. And as noted in "NPV<0", there are no instances in which the NPV of Scenario 1 was negative. A similar result is true for the comparison of the two build-up policies. The NWOM case shows a slightly more challenging picture. Although build-up 1 again outperformed the myopic policy, there were negative NPVs recorded in 8% of the scenarios.

The most striking feature of Table 5 is with respect to the standard deviation. In the presence of only PWOM, results are as expected, and variability is fairly slight. On the contrary, when both positive and negative WOM are present, there is a tremendous amount of variability. This indicates how operational changes might have unintended effects. Front end production, which increases holding costs, could at the same time reduce backlogged demands and its negative impacts. However, front end production also delays any influences of WOM, which influences the growth of demand throughout the process. The impact of these interwoven influences is evidenced in the standard deviation of NPV.

4.2 Impact of Negative WOM

The introduction of negative WOM reduces the NPV of profit for all 3 policies. It reduces the NPV of profit overall by 44 % for the myopic policy, 48 % for build-up 1, and 19 % for build-up 2.The reduction is strongly impacted by the consumers' willingness to wait. If consumers are likely to continue to wait for an out-of-stock product, results are very predictable, but as that likelihood decreases, the results are much more variable.

Goldenberg *et al.* (2007) finds that for every percentage increase in consumer dissatisfaction, the NPV of diffusion outcomes drops by 1.8%. The reduction in NPV of profit that we describe in this paper is much larger than 1.8%. The model of Goldenberg *et al.* (2007) differs from the model described in this paper in two major ways: it describes a diffusion process that is not restricted by supply constraints and the consumer network is modelled using a small-world network. This indicates that supply restrictions and network structure have the potential to further increase the negative impact of negative WOM. It also highlights the importance of further analyzing the impact of network structure on the diffusion process.

Managerial Implications: Managers can easily underestimate the presence of negative WOM since only a small percentage of consumers report their complaints to the firm. The numerical analysis highlights the importance of estimating the volume and frequency of negative WOM, especially for managers that are faced with limited product supply and consumers that are not willing to wait. Not considering negative WOM can lead to wrong policy recommendations and misleading conclusions concerning the impact of operational parameters.

4.3 Effect of Build-Up Period Selection

We consider the issue of selecting the best build-up period, not a simple task. This might be difficult to achieve. Therefore, we now suggest how sensitive the average NPV of profit is with respect to the build-up periods in scenario models 3-6. To illustrate the point, in Figure 4 we show the impact of build-up period selection for a single demonstration case for each of the build-up models. What is of interest is the magnitude of the change in NPV as the number of build-up periods is increased.

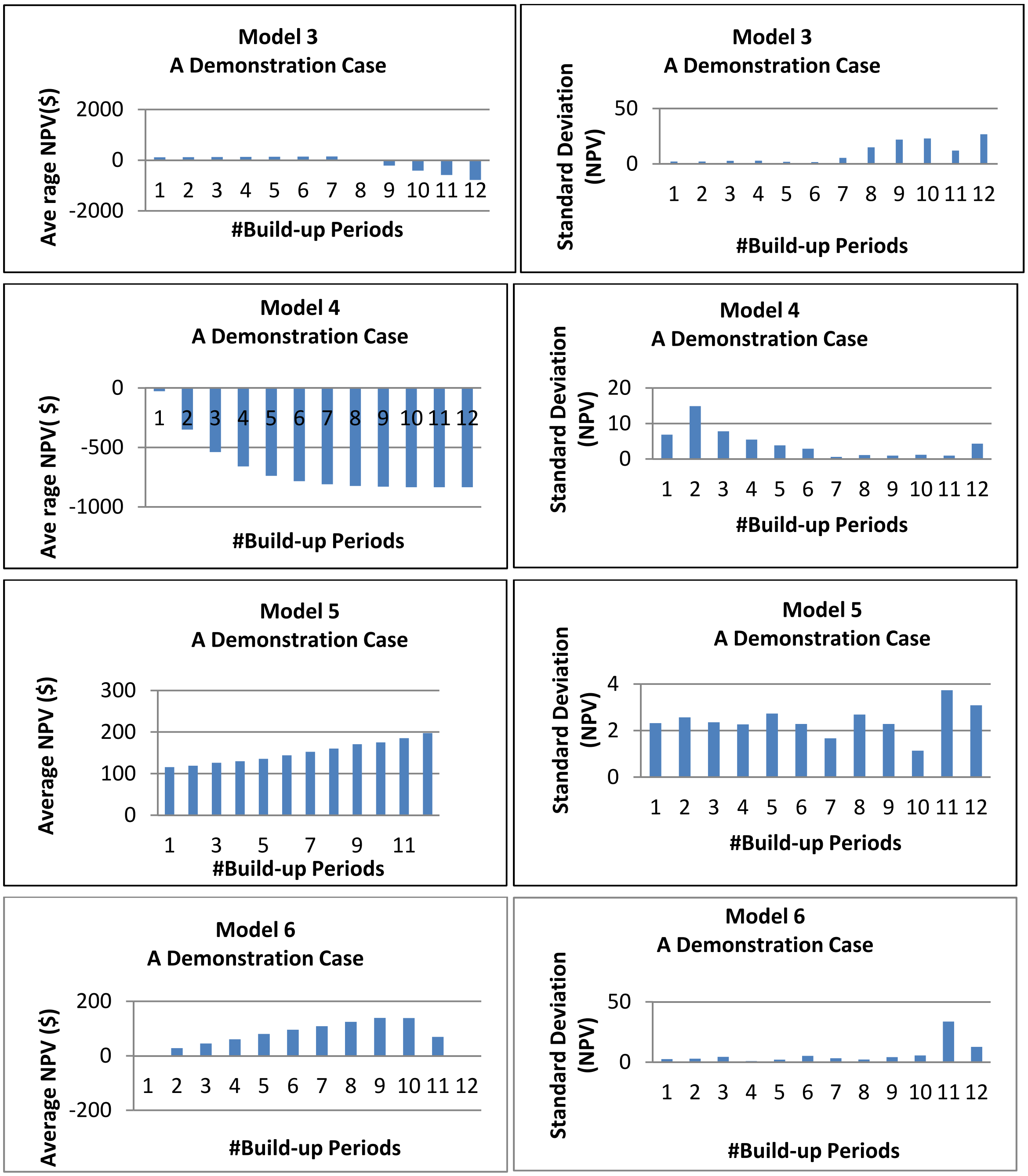

Figure 4. Effect of Build-up Period Selection

In scenario model 3 (build-up policy 1 with positive WOM), average NPV of profit is pretty stable for build-up periods up to 7 with tradeoffs on lost sales and holding costs.

However, for build-up periods above 7, average NPV drops quickly and standard deviation increases dramatically. As indicated in the examples, each model suggests a different sensitivity to build-up period selection. This underscores the importance of management being well-tuned to the implications of selection. Of the parameters under the control of management, the most sensitive one appears to be the selection of the length of the build-up period. In addition, the choice of build-up periods also affects the variability, and will play an important role in final NPV of profit.

Managerial Implications: Choice of the number of build-up periods is a critical management tool, particularly when considered along with the advertising strategy. A reasonable build-up period can increase stock availability – lessening the likelihood of stock-outs and rejected consumers once the product is launched. Consequently, NPV of profit can be increased significantly. However, there are also disadvantages to long build-ups. When negative WOM is present for build-up 1, consumers who receive advertising and want to buy the product before the product is launched can become adverse voices. In addition, uncertainty in the NPV tends to increase with longer build-up periods.

4.4 Production-Sales Policy Summary

At a significance level of 5%, an ANOVA was conducted to determine whether mean NPVs of the three production-sales policies are significantly different. The results indicate statistical significance with $F_{(3,1724)} = 407.21$, $p < 0.0001$. Also, a post-hoc Tukey's pairwise mean comparison was applied to rank the three policies. Tables 6.a and 6.b provide a brief summary of the findings for the three policies investigated. When rankings are shown, '1', '2' and '3' indicate the best, second best, and worst performing policies, respectively. Column 1 indicates the general performance over all 432 scenarios. Column 2 identifies the number of scenarios in which a negative NPV resulted when the best build-up period is chosen; this and column 3 summarize results for the best-build-up case – column 3 shows the minimum, average, and maximum NPV over the 432 scenarios. If the best build-up period is not selected, then we must consider column 4, which indicates the range of values resulting. Finally, column 5 summarizes the implications of the number of build-up periods for each model.

	Average Performance Rankings	# of Negative NPVs in Best Build-up Results (out of 432 cases)	Min/Ave/Max Best Build-up Results (rankings)	Min/Ave/Max Average Case Results (rankings)	# of Build-up Periods
Model 1 - Myopic	3	0	45/307/572 (2/3/3)	45/307/572 (2/2/2)	N/A
Model 3 – Build-up Policy 1	2	36	-468/431/676 (3/2/2)	-727/187/391 (3/3/3)	NPV - very sensitive
Model 5 – Build-up Policy 2	1	0	444/568/785 (1/1/1)	46/336/665 (1/1/1)	NPV – smooth concave

Table 6.a. General Performance Summary Under Positive WOM

In practice, when only PWOM is considered, it appears that build-up 2 is the most stable policy. Among the best performers, losses are avoided in all instances. The range of NPV's is fairly small, 341 (785-444). In all comparisons (min, max, and average), build-up 2 dominates both myopic and build-up 1. This suggests that delay in both production and marketing is worth considering, and in fact, even when the optimal number of build-up periods is not selected, build-up 2 has good results (NPV being smooth and concave). On the other hand, build-up 1 results in generating a negative NPV on occasion, and significant losses occur if there are too many build-up periods. Inventory build-ups, along with delayed sales have a dramatic impact on NPV.

In the presence of both positive and negative WOM, these results are exacerbated. Build-up 2 is again the most stable. And notably, the myopic policy realizes some negative NPV results, owing to the negative impacts of backlogs. Interestingly, long build-ups in build-up 1 are never practical, a consequence primarily of unsatisfied waiting customers. Not a surprise, NPV in the presence of NWOM is always lower than NPV without NWOM.

For the positive WOM scenarios, model 5 is the best overall, and very consistent. In no case did either model 1 or model 5 result in a negative NPV. Additionally, model 5 proves to be a very consistent performer and relatively insensitive to the choice of build-up periods. Model 3 seems to be an impractical option, from the standpoint of maximizing NPV of profit. In this table, we also note the importance of proper selection of build-up periods. Even for model 5, the range of outcomes in the average case is almost double that versus the best case. In the presence of both positive and negative word-of-mouth, similar results follow. Model 6 is the only environment with no negative NPV of profit.

	Average Performance Rankings	# of Negative NPVs' in Best Build-up Results (out of 432 cases)	Min/Ave/Max Best Build-up Results (rankings)	Min/Ave/Max Average Case Results (rankings)	Build-up Issues
Model 2 - Myopic Policy	2	55	-20/171/434 (2/2/3)	-20/171/434 (2/2/2)	N/A
Model 4 – Build-up Policy 1	3	228	-1043/-196/636 (3/3/2)	-1082/-374/361 (3/3/3)	Not practical
Model 6 – Build-up Policy 2	1	0	191/434/640 (1/1/1)	14/238/391 (1/1/1)	NPV – smooth concave

Table 6.b. General Performance Summary under Positive and Negative WOM

Managerial Implications: Overall, build-up policy 2 is the best policy among the ones studied in this paper. In our analysis, this policy leads to the best results overall in the case of only positive WOM as well as the case of positive and negative WOM. Furthermore, it generates the highest average NPV of profit when decision-makers can chose the optimal number of build-up periods as well as when this is not the case. In none of the cases that we studied did this policy lead to a negative NPV of profit.

5. Summary, Conclusions and Future Research

In this paper, we develop and implement an agent-based modeling and simulation approach to compare the impact of three supply chain production-sales policies and negative word-of-mouth on the supply restricted diffusion process of a new generic product and the NPV of profit generated by this product. Through a comprehensive computational experiment and extensive computational studies, we determine "optimal" supply chain production and sales policies.

We show that build-up 2 performs consistently well in the case of positive WOM as well as in the case of positive and negative WOM and that it is relatively insensitive to changes in build-up periods. Results of our computational study emphasize the importance of simultaneously considering marketing and operations processes to develop policies for sales and production of new products.

It is evident from the analysis that negative WOM plays a large role in supply restricted new product diffusion processes. Not considering negative WOM can lead to poor policy recommendations, incorrect conclusions concerning the impact of operational parameters on the policy choice, and suboptimal choice of build-up periods. Negative WOM has an impact that is especially strong if the myopic policy or build-up 1 is used and if consumers are not willing to wait for the product. Supply restrictions strongly increase the negative impact of negative WOM on NPV of profit. Therefore, considering the impact of negative WOM is especially important for firms faced with high product substitutability and capacity constraints. Further exploring and understanding the role of negative WOM in supply restricted product diffusion processes is of utmost importance in order to come up with reliable heuristics that managers can follow. In order to create a parsimonious model, we made several assumptions concerning the diffusion process: consumers only differ in the number of social of links but not in other characteristics; the consumer social network is assumed to be a random network, product rejecters and dissatisfied adopters communicate the same level of negative WOM, and the parameters depicting marketing activities and WOM are fixed for all consumers. Future research could explore how sensitive model results are to these assumptions. Furthermore, we are planning to extend the scope of the current study beyond a focal firm and include supply chain partners.

References

Alderson, D. L. (2008). Catching the "Network science" bug: Insight and opportunity for the operations researcher. *Operations Research, 56*, 1047-1065.Anderson, E. W. (1998).
Customer satisfaction and word of mouth. *Journal of Service Research, 1*, 5-17.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research, 4*, 291-295.

Baldwin, J. S., Allen, P. M., & Ridgway, K. (2010). An evolutionary complex systems decision-support tool for the management of operations. *International Journal of Operations and Production Management, 30*, 700-720.

Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., & Wallace, M. (2008). The effects of the social structure of digital networks on viral marketing performance. *Information Systems Research, 19*, 273-290.

Barabasi, A.-L. (2002). *Linked: The New Science of Networks*. Cambridge, MA: Perseus.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science, 15*, 215.

Bass, F. M. (2004). Comments on "A new product growth for model consumer durables". *Management Science, 50*, 1825-1832

Bunn, D. W., & Oliviera, F. S. (2007). Agent-based analysis of technological diversification and specialization in electricity markets. *European Journal of Operational Research, 181*, 1265-1278.

Emmanouilides, C. J., & Davies, R. B. (2007). Modelling and estimation of social interaction effects in new product diffusion. *European Journal of Operational Research, 177*, 1253-1274.

Garber, T., Goldenberg, J., Muller, E., & Libai, B. (2004). From density to destiny: Using spatial dimension of sales data for early prediction of new product success. *Marketing Science, 23*, 419-428.
Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research. *Journal of Product Innovation Management, 22*, 380-398.
Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing, 73*, 1-13.
Goldenberg, J., Libai, B., Moldovan, S., & Muller, E. (2007). The NPV of bad news. *International Journal of Research in Marketing, 24*, 186-200.
Goldenberg, J., Libai, B., & Muller, E. (2002). Riding the Saddle: How Cross-Market Communications Can Create a Major Slump in Sales. *Journal of Marketing, 66*, 1-16.
Griffin, A. (1997). PDMA resarch on new product development practices: Updating trends and benchmarkikng best practices. *Journal of Product Innovation Management, 14*, 429-458.
Guenther, M., Stummer, C., Wakolbinger, L. M., & Wildpaner, M. (2010). An Agent-Based simulation approach for the new product diffusion of a novel biomass fuel. *Journal of the Operational Research Society, Forthcoming*.
Harrison-Walker, L. J. (2001). The measurement of word-of-mouth communication and an investigation of service quality and customer commitment as potential antecedents. *Journal of Service Research, 4*, 60.
Hart, C. W., Heskett, J. L., & Sasser, W. E. J. (1990). The profitable art of service recovery. *Harvard Business Review, 68*, 148-156.
Hauser, J., Tellis, G. J., & Griffin, A. (2006). Research on innovation: A review and agenda for marketing science. *Marketing Science, 25*, 687.
Higuchi, T., & Troutt, M. D. (2004). Dynamic simulation of the supply chain for a short life cycle product--lessons from the Tamagotchi case. *Computers & Operations Research, 31*, 1097-1114.
Ho, T.-H., Savin, S., & Terwiesch, C. (2002). Managing demand and sales dynamics in new product diffusion under supply constraint. *Management Science, 48*, 187-206.
Jain, D., Mahajan, V., & Muller, E. (1991). Innovation diffusion in the presence of supply restrictions. *Marketing Science, 10*, 83-90.
Jiang, Z., Bass, F. M., & Bass, P. I. (2006). Virtual Bass Model and the left-hand data-truncation bias in diffusion of innovation studies. *International Journal of Research in Marketing, 23*, 93-106.
Kamrad, B., Lele, S. S., Siddique, A., & Thomas, R. J. (2005). Innovation diffusion uncertainly, advertising and pricing policies. *European Journal of Operational Research, 164*, 829-850.
Kumar, S., & Swaminathan, J. M. (2003). Diffusion of innovations under supply constraints. *Operations Research, 51*, 866-879.Los Angeles Times. (2007). Sony to cut game workers in U.S.*, June 7*.
Ma, T., & Nakamori, Y. (2005). Agent-based modeling on tehnological innovation as an evolutionary process. *European Journal of Operational Research, 166*, 741-755.
Mahajan, V., Muller, E., & Bass, F. M. (1990). New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing, 54*, 1-26.
McCarthy, K. (2007). The science and discipline of word-of-mouth marketing. *MSI Reports 07-301*, 15-16.

Mesak, H. I., Bari, A., Babin, B. J., Birou, L. M., & Jurkus, A. (2011). Optimum advertising policy over time for subscriber service innovations in the presence of service cost learning and customers' disadoption. *European Journal of Operational Research, 211*, 642-649.

Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: An introduction to computational models of social life* (illustrated edition ed.). Princeton, N.J.: Princeton University Press.

Mizerski, R. W. (1982). An attribution explanation of the disproportionate influence of unfavorable information. *Journal of Consumer Research, 9*, 301-310.

New York Times. (2000). Play Station Sales Zoom In.

Nilsson, F., & Darley, V. (2006). On complex adaptive systems and agent-based modelling for improving decision-making in manufacturing and logistics settings. *International Journal of Operations and Production Management, 26*, 1351-1373.

North, M. J., & Macal, C. M. (2007). *Managing Business Complexity*. New York, N.Y.: Oxford University press.

Parunak, V. D., Savit, H., & Riolo, R. L. (1998). Agent-based modeling vs. equation-based modeling: A case study and user's guide. *Lecture notes in computer science, 10*, 1354.

Rahmandad, H., & Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science, 54*, 998-1014.

Rogers, E. M. (2003). *Diffusion of Innovations* (5 ed.). New York, NY: Free Press.

Simon, H., & Sebastian, K.-H. (1987). Diffusion and advertising: The german telephone campaign. *Management Science, 33*, 451-466.

Stonebraker, J., S., & Keefer, D., L. (2009). OR practice---modeling potential demand for supply-constrained drugs: A new hemophilia drug at Bayer biological products. *Operations Research, 57*, 19-31.

Sultan, F., Farley, J. U., & Lehmann, D. R. (1990). A meta-analysis of applications of diffusion models. *Journal of Marketing Research, 27*, 70-77.

Swami, S., & Khairnar, P. (2006). Optimal normative policies for marketing of products with limited availability. *Annals of Operations Research, 143*, 107-121.

TARP, T. A. R. P. (1982). Measuring the grapevine consumer response and word-of-mouth. In *The Coca-Cola Company*. Washington, DC: Technical Assistance Research Programs.

TARP, T. A. R. P. (1986). Consumer complaint handling in America: An update study. In. Washington, DC: White House Office of Consumer Affairs.

Toubia, O., Goldenberg, J., & Garcia, R. (2008). A new approach to modeling the adoption of new products: Aggregated diffusion models *MSI Working Paper Series, 08*, 65-81.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. *Journal of Consumer Research, 34*, 441-458.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*, 440-442.

Xiaoming, Y., Cao, P., Zhang, M., & Liu, K. (2011). The optimal production and sales policy for a new product with negative word-of-mouth. *Journal of Industrial and Management Optimization, 7*, 117-137.

Yan, H.-S., & Ma, K.-P. (2011). Competitive diffusion process of repurchased products in knowledgeable manufacturing. *European Journal of Operational Research, 208*, 243-252.

Yáñez, F. C., Frayret, J. M., Léger, F., & Rousseau, A. (2009). Agent-based simulation and analysis of demand-driven production strategies in the timber industry. *International Journal of Production Research, 47*, 6295 – 6319.