4 Targeting and timing promotional activities for the takeoff of new products

Many marketing efforts are directed at promotional activities that support the launch of new products. Promotional strategies may play a crucial role in the early stages of the product life cycle, and determine to a large extent the diffusion of the new product. This chapter proposes an agent based model in order to simulate the efficacy of different promotional strategies that support the launch of a product. The article focuses in particular on the targeting and the timing of the promotions. The results of the simulation experiments indicate that diffusion dynamics are highly affected by promotional activities. The findings indicate that: (1) the absence of promotional support and/or a wrong timing of the promotions may lead to the failure of product diffusion; (2) the optimal targeting strategy is to address distant, small and cohesive groups of consumers; and (3) the optimal timing of a promotion differs between durable categories (white goods, such as kitchens and laundry machines, versus brown goods, such as TVs and CDs players). These results contribute to the planning and the management of promotional strategies supporting new product launches.

4.1 Introduction

A major part of firms’ activities consists of introducing new products or new technologies into the market. However, these activities introduce a considerable amount of risk to the firm because introducing a new product into a market is a highly unpredictable mission. The initial phase of market penetration is a critical moment for the future diffusion of the product. A fast and substantial takeoff can guarantee a

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9 The work of this chapter is based on Delre et al. (2007a).
competitive advantage, set up a wave of contagious consumptions, and thereby determine whether the product becomes a hit or a flop (Golder and Tellis, 2004; Mahajan and Muller, 1979). Promotional activities may support these crucial phases of the diffusion process. A substantial part of the marketing efforts, in particular promotions, is therefore directed at stimulating the initial diffusion of a new product.

Despite the large efforts involved in promotional planning, and despite the fact that a promotion strategic plan undoubtedly has a positive effect on the diffusion curve, the mission remains extremely complex and highly unpredictable. In particular, it remains unclear what is the optimal targeting strategy and what is the right timing for promotional mass media campaigns. There is no empirical or theoretical literature available to determine the optimal promotion strategy to enhance consumer adoptions at the crucial time that anticipates the takeoff of the diffusion process. This chapter contributes to the extant literature by proposing an agent based model for timing and targeting strategic decisions and simulating the effects of promotion on various settings of new product introductions.

Computational and agent based models provide a powerful tool to study micro-macro dynamics systematically. Studies using this methodology often focus on how macro dynamics emerge from the individual decisions of many individuals, and how these resulting macro dynamics feedback to individual decision-making (For an overview on agent based computational economics see http://www.econ.iastate.edu/tesfats/ace.htm). One field of application aims at simulating the diffusions of new products into a network of connected consumers that decide whether to adopt them or not (Alkemade and Castaldi, 2005; Deffuant et al. 2005; Delre et al. 2007b; Delre et al. 2007c). The agent based modelling approach permits the testing of different conditions under which a diffusion can either succeed or fail, and facilitates the identification of the precise time when a product takes off. The agent based model used in this chapter incorporates the effects of promotions on consumer adoption and on the takeoff of the new product. The simulation model permits the assessment of the effects of promotional strategies on the final market penetration and on the time of the takeoff. In this way, the model identifies the best targeting and timing conditions.

Concerning targeting, this chapter assesses the relative effectiveness of igniting the diffusion by targeting groups of consumers differing in size. Targeting many small
groups in distant places of the potential market (throwing gravel) outperforms targeting a small number of very large groups (throwing rocks). When throwing gravel, the diffusion is advanced both by the social influence that these groups exert on their neighbours and by the spread of information throughout the entire network of consumers.

Concerning timing, the study investigates the conditions under which mass media promotional campaigns stimulate the takeoff of the diffusion and explores how this external influence affects this takeoff and the final diffusion. In line with previous research (Eliashberg et al. 1989; Stremersch et al. 2003), this study indicates that takeoffs occur much earlier for brown goods, such as TVs and CD players, than for white goods, such as kitchens and laundry machines. Moreover, this article demonstrates that the appropriate timing of the promotion strategy is crucial, and that, in general, a premature mass media promotional campaign can lead to a flop. For white goods the best strategy is to promote the product when at least 10% of the market potential has already been reached. For brown goods, starting the promotion immediately after the launch is advisable.

The chapter is structured as follows. Section 4.2 briefly reviews the marketing literature on innovation diffusion and in particular on the analysis of takeoffs. Section 4.3 identifies the agent based model and the operational measurement used in order to identify the takeoffs. Section 4.4 presents the results of the simulation experiments. Finally, section 4.5 discusses the implications of the findings.

4.2 Background

Many scholars, especially in the marketing field, have studied the diffusion of new products (Mahajan et al. 2000). Often these studies consist of response models that explain empirical data on sales or the diffusion of a new product. These market response models succeed in describing the aggregate dynamics of new product entries, from their introduction until their complete penetration into their potential market. Usually the cumulative sales of new successful products, as the diffusion curve in Figure 4.1 shows, follow a typical S-shaped development: the diffusion starts slowly, after some time it
Effects of Social Networks on Innovation Diffusion and Market Dynamics

takes off showing a strong increase in growth-rate, and finally it saturates when a
certain level of marketing penetration has been reached (Rogers, 1995). At first, when a
new product is introduced into the market, sales increase slowly. During this time, sales
are mostly driven by external influences, such as promotions and mass media
advertising aimed at making the product to take off. Then, when a critical mass of
market penetration is reached, the sales suddenly take off and, at this particular point,
the sales growth-rate usually reaches its maximum. From this point on, sales are mostly
driven by internal influences, such as word-of-mouth (WOM) and social contagion,
until the majority of the market is penetrated. Finally sales decrease and then stabilize,
while the growth rate stabilizes and then decreases (Bass et al. 1995). These are usually
the empirical diffusion dynamics for successful market entries (Bass, 1969).

![S-shaped curve of the diffusion](image)

*Figure 4.1. The S-shaped curve of the diffusion.*

In the last 35 years, innovation diffusion models have become highly
sophisticated, including many other variables: price (Bass et al. 2000; Jain and Rao,
1990), potential market (Bass et al. 1994; Parker, 1992), promotion and advertising
(Dodson and Muller, 1978; Kalish et al. 1981). However, the general approach of these
works has rather been more descriptive than normative. By focusing on hypotheses-
testing supported by empirical analysis, these studies try to explain how, when and why
particular products diffuse into markets.

Whereas extant empirical studies mainly use data of successful diffusions in
order to explain the critical factors, most new products introduced into the market fail.
More than 90% of new product development projects proposed by R&D departments
are not approved by other departments in subsequent stages, and as a result will never become new products. Moreover, almost 50% of new products introduced into the market are complete failures and more than 70% of them do not reach their goals in terms of sales. Finally, most of these flops occur at the initial stages of the product entry (Business Week, 1993).

What does it make the success of a new product so difficult to achieve? Why is it so unpredictable? Arts et al. (2006) conduct a meta-analysis of the innovation diffusion field, showing that many studies report a multitude of explanatory determinants, often inconclusive and mixed. Moreover, extant research tends to focus on early determinants, such as the idea itself, on project-level determinants, such as the technologic compatibility between the product and the firm (Goldenberg et al. 2001), and on supply determinants, such as the number of firms introduced into the new market (Agarwal and Bayus, 2002).

In contrast, studies tend to focus less on market determinants, such as consumers’ preferences, needs and social factors, because these are less manageable and require research that is more costly. Especially in contexts of high social influence and fashionable environments, measuring or predicting these market determinants is very difficult. Markets are dominated by social influences e.g., individual decisions depend on what others consumers do. In this respect, a few strategic details can determine whether or not a new product becomes the object of a wave of adoptions driven by a positive WOM (Gladwell, 2000). An innovation can succeed in spreading out in a given population, if there is a combination of a small number of favourable events that convince a critical mass of consumers to adopt the new product. However, the same innovation can become a flop in the same population of consumers, if promoters miss these events or do not coordinate them properly.

Because of these market characteristics, promotional strategies represent crucial factors that can determine a break-through of a new product. Often promotional activities are associated with temporary price discounts aiming at increasing the sales of the product for a given period of time (Tellis, 1998). This chapter refers to promotional activities as any marketing effort that intends to enhance the takeoff of a product diffusion. These promotional activities include targeting and mass media campaigns, and usually form part of the external influence. They usually take place at the early
stages of a new product entry and they aim at creating the necessary critical mass to ignite, first, the takeoff, and then the social contagion effect that brings the majority of the market potential to adopt the product. The choice of the best targeting strategy represents a clear example: when launching a new product there is a sharp trade-off between two extremes of promotional strategies. First, the promotion strategy can be like *throwing rocks*, i.e. presenting the product to one or to a small number of big and cohesive groups of consumers in order to create social pressure to adopt the product (a group of friends has a strong influence on their neighbours and on others that belong or want to belong to that group). Second, the promotion strategy can be like *throwing gravel*, i.e. distributing the new product to numerous small groups throughout the population of potential consumers in order to spread as much information about the product as possible.

The selection of the optimal promotion is a very difficult task, especially because markets differ and promotional activities have to vary according to the category of products they promote. Literature has shown that the time of takeoffs highly varies for different kinds of durable categories (Golder and Tellis, 2004). Tellis et al. (2004) find that entertainment and information goods (brown goods) take off four times faster than durables, such as kitchen and laundry machines (white goods). For example, in the motion picture market, which represents an extreme case of fashionable market, the takeoff is extremely fast. Because of the huge promotion activity preceding the launch, the takeoff takes place before or immediately after the release of the product (Krider and Weinberg, 1998). Very often the box office analysis shows only the last part of the growth rate curve, usually an exponential decay (Eliashberg and Sawhney, 1996). For durable goods, takeoffs occur when a critical mass of innovators (and early adopters) becomes relevant enough to affect the majority of the potential market. However, such a critical mass varies according to the visibility, the prestige and the immediate satisfaction that the product brings to the consumers (Tellis et al. 2003). Market penetration at the time of takeoff varies from 3% to 16% (Rogers, 1995). In this work we adopt a standard operational measurement that identifies takeoffs depending on market penetration (Golder and Tellis, 1997; Tellis et al. 2004) (section 4.3.1). The simulation experiments replicate different market categories and the results of this study
are in line with previous research showing that takeoffs are faster for brown goods than for white goods.

4.3 The Model

The agent based model for innovation diffusion starts from the individual decision-making of the consumer. This model serves as a micro-level tool that specifies information flows as well as individual decisions, and aggregates these decisions at the macro-level of the market. Consumers are agents that are connected within a unique network. The nodes of this network are the consumers and each link between two nodes represents a relation between two consumers through which they can communicate. Such network can vary from completely regular ($r=0$) to completely random ($r=1$) (Watts and Strogatz, 1998). On the one hand, when the network is completely regular, agents are highly clustered and the information takes long time to travel from one node to another distant node. On the other hand, when the network is completely random, agents are not clustered at all and information, if any, is spread to all other nodes within a very short time. However, in between these two extremes the so-called “small-world area” exists. This area is still highly clustered while the information spreads very fast to all the clusters of the network (Amaral et al. 2000). This chapter adopts a slightly different variation of the Strogatz and Watts model, beginning with a regular lattice and adding a small percentage ($0.01 \leq r \leq 0.1$) of random links compared to the total number of links. This version of the model maintains the same properties of the Small-World networks (Newman, 2002; Newman and Watts, 1999). Many works have described how diseases and knowledge spread in Small-World networks (Cowan and Jordan, 2004; Newman, 2002; Newman and Watts, 1999). Delre et al. (2007b) propose how to adapt these models of diffusion to social and economic contexts. Because in this chapter we do not explicitly focus on how network structures affect diffusion patterns, we adopt a single fixed network structure, which can generally represent the connections among the consumers (for the values of the parameters see Table 4.3).

The agent decides whether or not to adopt the product and, if so, it communicates this to the other agents that are linked to it. In this way the diffusion
process continues through the network, simulating the wave of WOM. Agent $i$ adopts the new product if the individual utility that it obtains when consuming product $j$ is higher than the minimum level of utility that it requires:

$$U_{i,j} \geq U_{i,j,MIN}$$  \hspace{1cm} (4.1)

Agents are involved in the decision-making process if at least one of their neighbours has already adopted the product (WOM). In this case, they use a simple weighed utility of individual preference and social influence:

$$U_{i,j} = \beta_{i,j} \cdot x_{i,j} + (1 - \beta_{i,j}) \cdot y_{i,j}$$  \hspace{1cm} (4.2)

where

$$y_{i,j} = \begin{cases} q_j \geq p_j \Rightarrow 1 \\ otherwise \Rightarrow 0 \end{cases}$$  \hspace{1cm} (4.3)

$$x_{i,j} = \begin{cases} a_i \geq h_{i,j} \Rightarrow 1 \\ otherwise \Rightarrow 0 \end{cases}$$  \hspace{1cm} (4.4)

$$a_i = \frac{\text{adopters}}{\text{adopters} + \text{non-adopters}}$$  \hspace{1cm} (4.5)

$U_{i,j,MIN}$ specifies $i$'s minimum utility requirement and $U_{i,j}$ is the utility of agent $i$, when it adopts product $j$. The utility has two components that are threshold functions: individual preference $y_{i,j}$ and social influence $x_{i,j}$ of $i$'s personal network; $\beta_{i,j}$ weighs these two components and represents how strong the social influence of product $j$ is in the market. Concerning the individual part, $p_j$ is the individual preference of agent $i$ and $q_j$ is the quality of product $j$. Concerning the social influence part, $h_{i,j}$ is a threshold that determines the individual agent’s sensibility to its neighbours’ behaviour, and $a_i$ is the percentage of adopters in $i$’s personal network. Agents included in $i$’s personal network are called alters. If the fraction of adopters in $i$’s personal network is higher than $h_{i,j}$, the agent feels social influence, otherwise it does not. (For an analysis of how personal networks affect diffusion dynamics, see Delre et al. 2007b). The rationale of this formalization is the classic threshold mechanism of collective action: a consumer does
not feel social influence if only a few people around her/him behave in a particular way, but once the number of these people reaches a certain amount, he/she suddenly decides to change his/her mind and behaves differently (Granovetter and Soong, 1986).

Diffusion starts by launching a product into the population, which can take place in two different ways. First, a product reaches a percentage of the population, $e_1$, at the beginning of the simulation run. The agents that receive the product at the launching time are called seeds (Libai et al. 2005). Once these agents have adopted the product, at the following time step, other agents connected to them are also involved in the WOM process. Then, they too evaluate their utility according to (4.1) and decide whether or not to adopt the product. In this way the process of diffusion spreads out in the network of consumers. If this wave of adoption stops at a certain time, it means that given those conditions and the number of adopters at that time, either the non-adopters do not want to adopt or do not know about the product. The diffusion process cannot start again unless a new external promotion is organized. This kind of launch is used in order to analyze how different promotion strategies, such as targeting, affect the final marketing penetration (section 4.4.1).

A second way of launching a product is by mass media campaigns. This other kind of launch simulates mass media campaigns, allowing all agents to be involved in the decision-making (4.1) with probability $e_2$. We use this launch when analyzing how the timing of the promotional mass media campaigns dynamically affects the diffusion (section 4.4.2).

Formalizing the consumers’ decision-making in this way implies that agents have three possible stages: (a) non-aware; (b) aware and non-adopter; and (c) aware and adopter. In fact, they decide whether or not to adopt a product only after becoming aware of the product. The agents become aware of the product either when some of their friends have already adopted the product (by WOM) or when mass media campaigns have reached them. These two kinds of information flows are theoretically identical to the traditional internal and external influences of the Bass model. However, they differ in the sense that in their decision-making consumers explicitly consider two stages: becoming aware of and adopting the product. The model clearly distinguishes between the WOM process and the social influence of adopters on non-adopters. WOM is simply the spreading of product information, which makes consumers aware of the product
travelling from consumer to consumer. The social influence is the influence adopters exert on non-adopters at the local level. The more adopters are in a consumer’s network, the higher the social influence.

Finally, this agent based model is a re-interpretation of the classic innovation diffusion models based on a micro-formalization of the decision-making of the consumer. Classic diffusion models, such as the Bass model and its variations, imply that the role of internal influence often dominates the role of external influence, especially during the growth stage. In fact, the fits of these models to the S-shaped data of the sales of durable goods show that the biggest part of the market is penetrated as a result of internal influence (Mahajan, et al. 1995), or social contagion (Stremersch and Van den Bulte, 2004). When the diffusion curve is a typical S-shaped curve, the ratio between the estimates of external and internal influences often varies from 10 to 100 (Bass, 1969; Mahajan, et al. 1995). In line with these empirical results, this study restricts the analysis to high values of $\beta_{i,j}$ in order to guarantee a sufficient level of social influence. In particular, one can simulate both white good markets, such as kitchen and laundry machines (with $\beta_{i,j}$ varying from $N \sim (0.75, 0.01)$ to $N \sim (0.8, 0.01)$ and $h_{i,j}$ varying from $N \sim (0.35, 0.01)$ to $N \sim (0.4, 0.01)$) and brown good markets, such as TVs, CDs, VCRs (with $\beta_{i,j}$ varying from $N \sim (0.85, 0.01)$ to $N \sim (0.9, 0.01)$ and $h_{i,j}$ varying from $N \sim (0.2, 0.01)$ to $N \sim (0.25, 0.01)$).

In the simulation runs many parameters of the model are theoretically driven, and so they are not the object of analysis. This means that some assumptions have been made. Table 4.3 specifies the complete list of the parameters, their values and the underlying theoretical assumptions.

### 4.3.1 A given threshold for selecting takeoffs

Figure 4.2 presents a typical S-shaped diffusion curve. This curve simulates a market where social influence is quite strong ($\beta_{i,j} = N \sim (0.9, 0.01)$, $h_{i,j} = N \sim (0.3, 0.01)$ and $\epsilon_2 = 0.001$). The new product takes off somewhere between time step 30 and time step 40. In order to precisely identify a takeoff and its time, we follow the heuristic approach of Golder and Tellis (1997) and Tellis et al. (2003) by plotting the growth rate of the diffusion curve against the market penetration. Based on a visual threshold chosen ad
hoch, the precise time of a takeoff is when the growth rate overpasses this threshold for the first time. If $S_t$ is the number of agents that adopt a product at time $t$, the growth rate $g_t$, the market penetration $v_t$ and the takeoff threshold $T_t$ are as follows:

$$g_t = (S_t - S_{t-1}) / S_t$$

$$v_t = S_t / N$$

$$T_t = (1 - v_t)\gamma$$

Parameter $\gamma$ shapes the takeoff threshold and, following Golder and Tellis (1997) and Tellis et al. (2003), we select $\gamma$ in order to make the best prediction visually. Figure 4.3 shows an example. The first time the growth rate overpasses this threshold occurs when the market penetration is between 10% and 15% of the potential market. The model simulates the micro-level of the decision-making. Each time step may represent a short period of time, for example, a week, and consequently at each time step the growth rate remains relatively low. $S_t$ values are collected every 5 time steps, summing up the number of adopters $s_t$ of the previous 5 time steps: $S_t = \sum_{i=5}^{t} s_{t-i}$. Moreover, in order to avoid the risk of taking minor absolute growths for takeoffs because they resemble high relative growths, takeoffs are collected only if $g_t > 0.005$. For this reason the first and the last growth rate points that overpass the takeoff threshold are often not taken into consideration. Finally, we use $\gamma = 10$ for all the simulation runs because this parameter fits all takeoff points of the diffusion curves. The time to take off is the time between the market introduction of the new product and the takeoff. Figure 4.3 permits us to identify precisely that the time to take off is 40 time steps.
Figure 4.2. The market penetration $v_t$ at each time step.

Figure 4.3. The growth rate $g_t$ plotted against the market penetration $v_t$ and the threshold for the takeoff identification.

4.4 Simulation Experiments and Results

First, we investigate different targeting campaigns varying the dimension and the targets of the promotion. Second, we explore issues regarding the right timing of post-launch mass media promotional campaigns. These issues provide insights about the optimal timing for different product categories and different markets.

4.4.1 Targeting strategy: throwing rocks vs throwing gravel

The simulations explore the diffusion patterns in a market where the decision of each consumer highly depends on what other consumers do ($\beta_{i,j} = N(0.8, 0.01)$ and $h_{i,j} = N(0.35, 0.01)$). The launching targeting strategy, throwing gravel, consists of throwing the product into the population while selecting randomly a given number of seeds who receive the product. This method simulates a targeting campaign in which the product is randomly assigned to a number of consumers. In this way, we study how big the targeting promotion has to be in order to ignite the social contagious process. At the end of a simulation, all other parameters being equal, the final number of adopters depends
on how many seeds are selected during the launch and on how they are connected to each other. So we vary $e_j$ at the beginning of the simulations and we collect the values of the market penetration $v_t$ at the end of the simulation runs. Figure 4.4 shows that in order to achieve a market penetration of over 75% of the potential market, it is necessary to select at least 8% of the consumers as seeds. When increasing the number of seeds up to 15% of the population, one obtains a relevant marginal success in the final market penetration. However, such a strategy is unrealistic because of the high costs involved; managers should therefore decide to plan alternative targeting strategies.

![Figure 4.4. Market penetration $v_t$ and marginal effect varying the number of seeds at moment of launch.](image)

A possible alternative strategy is the *throwing rocks* strategy. This approach consists of targeting one or a small number of big groups of highly connected consumers. With this strategy a manager aims at igniting the diffusion in a precisely indicated area of the network so that the neighbours of that area are being subjected to more social influence to adopt the product. However, in this way the launch risks remaining localized and many other areas of the network may not become aware of the new product. A manager has to find the right balance between the gravel strategy and the big rock strategy. In fact, the simulation results show that neither of the two extreme strategies is the most efficient in launching a product. One obtains the highest number of adopters (largest market penetration) if one balances the two extreme targeting strategies by selecting part of the seeds with the throwing gravel strategy and the other part with the throwing rock strategy. In this way, the diffusion dynamics are facilitated by both the spreading of the information and the social influence that adopters exert.
when they are in clustered cohesive groups. Here the task of the manager is to organize the centres of adoption in different places of the market in order to ignite a big diffusion throughout the entire market. The model can be used to ascertain the desired number and the size of these groups. Figure 4.5 shows what happens when distributing the same number of seeds ($e_I = 0.04$) but in groups of different sizes. The outcomes are very different and the best strategy, as already mentioned, is to find a right balance between the two extremes. In this case (with 3000 agents and 120 seeds, $\beta_{i,j} = N-(0.8, 0.01)$ and $h_{i,j} = N-(0.35, 0.01)$), the best strategy consists of focusing on 40 groups, each one with 3 consumers.

![Figure 4.5. The market penetration $v_I$ at the end of each simulation run balancing the throwing gravel strategy and the throwing rocks strategy.](image)

This result is robust for a wide range of parameters. When we set the parameter values in such a way that the market penetration at the end of the simulation move from 0.4 to 0.7 ($\beta_{i,j}$ varying from 0.7 to 0.9; $h_{i,j}$ varying from 0.3 to 0.4 and $e_I$ varying from 3% to 5%), we obtain similar outputs. Moreover, when we tune the parameters in such a way that the market penetration becomes higher, the best targeting strategy appears to be to select more and smaller groups. On the other hand, when there is a lower market penetration, the best targeting strategy tends to be one that aims at fewer but bigger groups.

Finally, Figure 4.5 shows that the standard deviations of the different runs increase significantly when targeting more small groups. This indicates that the extreme throwing gravel strategy (targeting as many groups as possible, i.e. single consumers not connected to each other) is also the riskiest strategy.
4.4.2 The timing of post launch mass media campaigns

Mass media strategies affect the immediate future of the launch of a new product. Usually managers promote the product positioning seeds at the moment of launch and increasing the strength of mass media messages during the post launch. In this way, the process of social contagion can fully develop, and many consumers have the opportunity to become aware of the new product. However, social contagion and marketing effort may also overlap, and often it is not clear which of the two effects generates the wave of adoption. In fact, many works have already demonstrated that innovation diffusions can be explained by marketing effort rather than by social contagion (Van den Bulte and Lilien, 2001) and that it is sufficient to assume a consumer’s heterogeneity in order to generate S-shaped adoption curves (Chatterjee and Eliashberg, 1990).

The simulation model used allows us to test separately the different effects of mass media campaigns on the diffusion, providing insights into the optimal timing of the start of these campaigns. Figures 4.6 and 4.7 show the results on early and later mass media campaigns, respectively. In order to simulate mass media promotional campaigns, we vary the value of \( e_2 \), i.e. the probability of informing agents about the new product, for a fixed period of time steps. Concerning early mass media campaigns, we set \( e_2 = 0.001 \) at the beginning of the diffusion. Then, from time step 0 until time step 10, we simulate the mass media campaign under two circumstances: \( e_2 = 0.005 \) (weak campaign) and \( e_2 = 0.05 \) (strong campaign). For these simulation runs we set the model to \( \beta_{ij} = N\sim(0.9, 0.01) \) and \( h_{ij} = N\sim(0.4, 0.01) \). The results (Figure 4.6) show that a strong mass media campaign, taking place at the beginning of the diffusion, has drastic negative effects on the diffusion. In this case the product is promoted too soon and too strongly, the diffusion does take off very soon but it reaches a low final market penetration. This is due to the fact that too many consumers have become aware of the product at the beginning of the diffusion. They decide not to adopt the product because not enough other consumers have done so yet. Then, there are many groups of consumers that, making this negative decision at the beginning of the diffusion, exert a negative social influence as a result of which the market penetration remains low.
Contrarily, if the mass media campaign is not so strong, the diffusion is positively supported. The take off occurs later compared to the strong campaign but the final market penetration is considerably higher.

Figure 4.7 shows what happens in the opposite situation, when the mass media campaigns take place later. The diffusion starts with $e_2 = 0.001$ and then, from time step 20 until time step 50, a later mass media campaign is simulated by $e_2 = 0.002$ (weak campaign) or $e_2 = 0.005$ (strong campaign). It is clear that, compared with the absence of extra mass media promotional campaigns, the weak campaign does not bring substantial advantages to the diffusion curve. Contrarily, the strong campaign helps the growth phase of the diffusion curve letting the new product to take off sooner. This indicates that a weak mass media campaign runs the risk of being useless, especially when the product has already taken off. At that stage, consumers have become aware of the product mostly via WOM, and thus a weak mass media campaign runs the risk of not being noticed.
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Figure 4.7. Diffusion curves for different mass media campaigns (strong $e_2 = 0.008$ and weak $e_2 = 0.002$) placed at a later stage of the diffusion (from time step 20 until time step 50).

4.4.3 Different markets: white goods vs brown goods

Research has shown that takeoffs occur at different times for different categories of goods. Tellis et al. (2003) adopt the distinction between white goods and brown goods. White goods are durables that are not very visible, such as kitchens and laundry machines. Brown goods, such as TV, DVD and CD players, are much more visible, and give more instant gratification. Tellis et al. (2003) observe that brown goods take off much faster than white goods. White goods need more time to take off because they are usually more expensive and they involve more risk. Thus, contagious processes driven by social influence begin later, when the market penetration is higher and the advantages of the product are more evident. Contrarily, brown goods take off faster because they involve less risk; they are more fashionable and often more visible. Consequently, in the case of brown goods, social influence processes take place very close to the moment of launch. The model implements the distinction between these product categories by varying the $i,j$ and the $h_{i,j}$ parameters in the individual decision-making of the agents. When $i,j$ is high and $h_{i,j}$ is low, we simulate a brown good market. The individual decision-making highly depends on what neighbours decide to do, and even if just a few neighbours adopt the product, the agents perceive social
influence. At this stage agents are very susceptible and the market becomes fashionable. When $\beta_{ij}$ is low and $h_{ij}$ increases, white good markets are simulated. Because the individual preferences weigh more heavily in the individual decision of the agents and more neighbours have to adopt the product for an agent to perceive social influence, such a market becomes less susceptible to contagious processes. We conduct simulation experiments for the two categories and identify take offs from the simulated diffusion curves. Figures 4.8 and 4.9 show the growth rate curves of white and brown goods respectively that manage to take off without any extra mass media promotional activity.

The values of the parameters in order to simulate brown goods versus white goods are the default values specified in Table 4.3. It is clear that brown goods ($v_\gamma = 0.101$) take off more quickly than white goods ($v_\gamma = 0.136$).

![Figure 4.8. Takeoff identification for white goods.](image)

![Figure 4.9. Takeoff identification for brown goods.](image)
We vary extra factors within the model to investigate how extra mass media promotional campaigns can be used in both product categories in order to enhance the takeoff time and/or the growth stage after the takeoff. In order to do so, we increase the value of $e_2$ (from $e_2 = 0.001$ to $e_2 = 0.05$) for a given period of time (10 time steps) in order to determine the effect of this extra campaign when this is placed at different times of the diffusion. Tables 4.1 and 4.2 (white and brown goods, respectively) show whether the growth rate $g_t$ overpasses the threshold curve and with which value, the corresponding market penetration $v_t$, the time of takeoff $t$, and the final market penetration at the end of the simulation run.

The timing of the promotional activity is crucial for both product categories. Under the given conditions, the takeoff of white goods is anticipated when the extra mass media promotional campaign takes place at any time before the takeoff. In fact, Table 4.1 shows that when the extra campaign is placed between the launch and the takeoff (in the case of no extra campaigns the takeoff occurs at time step 40 and at market penetration $v_t=0.175$) this campaign always succeeds in anticipation the takeoff. However, the results show that extra mass media campaigns at this early stage of the diffusion have a negative effect on the final market penetration (see also Figure 4.6 in section 4.4.2). This negative effect can amount up to 20% of the potential market: the final market penetration is 0.772 with no extra campaign and it becomes 0.568 when the campaign takes place between time steps 30 and 40. This negative effect is always highly relevant when the extra mass media campaign takes place at any time before the 10% of the market penetration is reached. Brown goods show different dynamics. Under the conditions that simulate brown good markets, we always observe a faster take off when a promotional activity of the same strength is performed. Compared to the no extra promotional campaign, the different timings of the same mass media promotional campaign anticipates the time of takeoff and they did not have negative effects on the final market penetration. In fact, final market penetration values were stable around 0.95 for all the conditions. With no extra campaign the take off occurs at time step 27 and at $v_t=0.112$. The takeoff can be anticipated until time step 13 and $v_t=0.03$ without any negative effects on the final market penetration.
We can summarize these results by pointing out that it is always possible to enhance the takeoff of new products in both brown good markets and white good markets. However, in terms of final market penetration, this is very risky for white good markets. For brown good markets, mass media promotional campaigns are very efficient when they take place just after the launch. In this way, they have the effect of anticipating the takeoff without losing any potential market.

Table 4.1
Takeoff identification for white goods with different timings of the same mass media campaign.

<table>
<thead>
<tr>
<th>Takeoff</th>
<th>( g(t) )</th>
<th>( v(t) )</th>
<th>( t )</th>
<th>Final market penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>No prom</td>
<td>Yes</td>
<td>0.18</td>
<td>0.175</td>
<td>40</td>
</tr>
<tr>
<td>Prom 10-20</td>
<td>Yes</td>
<td>0.892</td>
<td>0.031</td>
<td>12</td>
</tr>
<tr>
<td>Prom 20-30</td>
<td>Yes</td>
<td>0.552</td>
<td>0.064</td>
<td>23</td>
</tr>
<tr>
<td>Prom 30-40</td>
<td>Yes</td>
<td>0.576</td>
<td>0.064</td>
<td>33</td>
</tr>
<tr>
<td>Prom 40-50</td>
<td>Yes</td>
<td>0.3</td>
<td>0.117</td>
<td>31</td>
</tr>
<tr>
<td>Prom 50-60</td>
<td>Yes</td>
<td>0.372</td>
<td>0.113</td>
<td>33</td>
</tr>
</tbody>
</table>

Table 4.2
Takeoff identification for brown goods with different timings of the same mass media campaign.

<table>
<thead>
<tr>
<th>Takeoff</th>
<th>( g(t) )</th>
<th>( v(t) )</th>
<th>( t )</th>
<th>Final market penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>No prom</td>
<td>Yes</td>
<td>0.396</td>
<td>0.112</td>
<td>27</td>
</tr>
<tr>
<td>Prom 10-20</td>
<td>Yes</td>
<td>0.923</td>
<td>0.028</td>
<td>13</td>
</tr>
<tr>
<td>Prom 20-30</td>
<td>Yes</td>
<td>0.469</td>
<td>0.085</td>
<td>20</td>
</tr>
<tr>
<td>Prom 30-40</td>
<td>Yes</td>
<td>0.437</td>
<td>0.085</td>
<td>26</td>
</tr>
<tr>
<td>Prom 40-50</td>
<td>Yes</td>
<td>0.488</td>
<td>0.086</td>
<td>28</td>
</tr>
<tr>
<td>Prom 50-60</td>
<td>Yes</td>
<td>0.333</td>
<td>0.113</td>
<td>28</td>
</tr>
</tbody>
</table>

4.5 Conclusion and Discussions

The results of this study indicate that the issue of how and when to conduct promotional activities is very important with respect to the diffusion dynamics of the product involved. Diffusions take off as a result of internal influences, such as social contagion, taking place in the network of consumers. Promotion strategies are meant to be the
sparks that start the fire. Our agent based model allows the implementation of different promotional activities and the observation of their effects on different kinds of markets. The results provide useful insights for managers who plan promotion strategies for the take off of new products.

The initial results show that targeting small cohesive groups of consumers in distant areas of the market potential is the optimal strategy. In this way, the manager maximizes the trade-off between the throwing rocks strategy, which ignites a single big centre of consumption that is highly visible to other consumers, and the throwing gravel strategy, which creates as many centres of consumption as possible in different areas of the marketing potential. This result contributes to the international diffusion literature (Chryssochoidis and Wong, 1998; Libai et al. 2005), suggesting that the strategic planning of seeding is a key determinant of the takeoff and the final market penetration of an innovation.

In addition, the timing of promotional activities has a strategic role in inducing a takeoff of the diffusion and in reaching a high market penetration. Here the manager has to determine the right time to introduce extra mass media campaigns. The results suggest that one should avoid both huge premature mass media campaigns and weak late campaigns. When a mass media campaign is very big and takes place just after the launch, consumers may decide too soon. In this case, many consumers decide not to adopt the product because not enough others consumers have done so yet. This hampers the diffusion substantially. When a weak campaign takes place too late, the marketing effort may be wasted, resulting in inefficiency because of overlap with the social contagion.

The time of takeoff is a central issue in the innovation diffusion literature. It has been shown that non-price determinants have a strong impact on the takeoff of new products (Agarwal and Bayus, 2002; Goldenberg, 2001). Whereas these works focus more on the supply side of the innovation, our simulation model concentrates on the demand side. The results contribute to the field by providing theoretical insights into how to manage mass media messages in order to accelerate the incubation of the diffusion before the takeoff. Moreover, the results constitute an additional theoretical contribution to the distinction among product categories and offer suggestions on how to position extra mass media promotional activities in different markets. The results
concerning the timing of extra mass media campaigns suggest that in white good markets, on the one hand, promotional campaigns can anticipate the takeoff time but these are also very dangerous because they risk to hamper the final diffusion. It is advisable to start a strong mass media campaign only if at least 10% of the market potential has already adopted the product. In the brown good market, on the other hand, the campaign accelerates the takeoff of the new product without damaging the final penetration.

This agent based model is highly flexible because it easily implements different promotional strategies and different market characteristics, while maintaining the main classic features of the innovation diffusion field (WOM versus mass media campaigns; individual preferences versus social contagion). However, the other side of the coin is that the model pays for this high flexibility with a high number of parameters (10 in total). In order to obtain robust results many of these parameters remain fixed and consequently many critical assumptions have to be made (see table 4.3). A fruitful and promising venue of research consists of calibrating agent based models by using laboratory experiments and surveys (Janssen and Ostrom, 2005). In this way the extant assumptions become less restrictive because the empirical evidence supports them. Therefore, agent based models might also become promising predictive tools. As such they may contribute to the normative validation of the innovation diffusion models and, more generally, to the analysis of social and economic phenomena.

<table>
<thead>
<tr>
<th>Name</th>
<th>Parameter</th>
<th>Values</th>
<th>Theoretical assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation runs</td>
<td>20</td>
<td></td>
<td>In order to make our results more robust, we ran 20 simulation runs per each condition. They report the average and, when necessary, the standard deviation of the different runs.</td>
</tr>
</tbody>
</table>
### Chapter 4: Targeting and timing promotional activities...

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time steps of the simulation run</td>
<td>500</td>
<td>In all simulation runs, the system converges to a steady state where no more adoptions are observed.</td>
</tr>
<tr>
<td>Number of agents ( N )</td>
<td>3000</td>
<td>None.</td>
</tr>
<tr>
<td>Number of shortcuts into the network</td>
<td>0.01</td>
<td>The global network structure is a “Small World”. Consumers are very clustered but information can travel fast through the network.</td>
</tr>
<tr>
<td>Minimum level of satisfaction of the agent ( i ) ( U_{i,j,MIN} )</td>
<td>Uniform distribution [0, 1].</td>
<td>None.</td>
</tr>
<tr>
<td>Personal preference of the agent ( i ) ( p_i )</td>
<td>Uniform distribution [0, 1].</td>
<td>None.</td>
</tr>
<tr>
<td>Quality of the product ( j ) ( q_j )</td>
<td>0.5</td>
<td>The product characteristics are neutral to consumers’ preferences. The likelihood that a given consumer likes the product is the same as the likelihood that she/he does not like it.</td>
</tr>
<tr>
<td>Takeoff threshold identification ( \gamma )</td>
<td>From 8 until 12, Default value: 10</td>
<td>The takeoff threshold decreases exponentially with marketing penetration. The more the marketing penetration, the more the decrease in the chances of observing a takeoff. Similar results are obtained with ( \gamma ) varying from 8 to 12.</td>
</tr>
<tr>
<td>Proportion of seeds (targeted consumers) ( e_1 )</td>
<td>Independent variable.</td>
<td>None.</td>
</tr>
</tbody>
</table>
Effects of Social Networks on Innovation Diffusion and Market Dynamics

<table>
<thead>
<tr>
<th>Probability of messages of mass media campaigns to reach a consumer</th>
<th>Independent variable. Default value: 0.001</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_2$</td>
<td>Strong mass media campaign: from 0.005 until 0.05</td>
</tr>
<tr>
<td></td>
<td>Weak mass media campaign: from 0.0005 until 0.002</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Personal threshold $h_{i,j}$ to neighbours influence</th>
<th>Independent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Default values for brown goods: $N\sim(0.3, 0.01)$; default values for white goods: $N\sim(0.4, 0.01)$.</td>
</tr>
<tr>
<td></td>
<td>Consumers are slightly more sensible to positive social influence (adoption) than negative social influence. They perceive social influence if more than 30% (brown goods) or 40% (white goods) of the consumers connected with them decide to adopt the product. (Alkemade and Castaldi, 2005; Granovetter and Song, 1986).</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Weight of individual part and social part of an agent $i$ in the utility function</th>
<th>Independent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{i,j}$</td>
<td>Default values for brown goods: $N\sim(0.1, 0.01)$; default values for white goods: $N\sim(0.25, 0.01)$</td>
</tr>
<tr>
<td></td>
<td>Consumers’ decision-making depends for the greater part on what other consumers do (internal influence). Consequently, diffusion curves in general and growth stages in particular are mainly driven by social contagion (Bass, 1969; Mahajan et al. 1995). The internal influence is stronger for brown goods than for white goods (Tellis et al. 2003).</td>
</tr>
</tbody>
</table>