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Targeting and timing promotional activities: An agent-based model for the takeoff of new products

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Abstract

Many marketing efforts focus on 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 a new product. This paper proposes an agent-based model to simulate the efficacy of different promotional strategies that support the launch of a product. The article in particular concentrates on the targeting and the timing of the promotions. The results of the simulation experiments indicate that promotional activities highly affect diffusion dynamics. The findings indicate that: (1) the absence of promotional support and/or a wrong timing of the promotions may lead to a 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.

Keywords: Diffusion of innovations; Agent-based model; Targeting strategies; Promotions; Takeoff of diffusions; Word-of-mouth; Social influence

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 launching 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 a product. A fast and substantial takeoff can guarantee a 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, therefore aims at stimulating the initial diffusion of a new product.

Despite the large efforts involved in promotional planning, and despite the fact that a strategic promotion plan undoubtedly has a positive effect on the diffusion curve, the mission remains extremely complex and highly unpredictable. In particular, the optimal *targeting* strategy as well as the right *timing* for promotional mass media campaigns remain unclear. No empirical or theoretical literature is available to determine the optimal promotion strategy to enhance consumer adoptions at the crucial time that anticipates the takeoff of the diffusion process. This paper 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.%20Iastate.edu/tesfats/

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ace.htm). One field of application aims at simulating the diffusions of new products into a network of connected consumers that decides whether or not to adopt them (e.g. Alkemade and Castaldi, 2005; Deffuant et al., 2005; Delre et al., 2006). The agent-based modeling 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 dealt with in this paper 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 paper 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 neighbors and 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 (Gatignon et al., 1989; Tellis 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 paper is structured as follows. Section 2 briefly reviews the marketing literature on innovation diffusion and in particular on the analysis of takeoffs. Section 3 identifies the agent-based model and the operational measurement used in order to identify the takeoffs. Section 4 presents the results of the simulation experiments. Finally, Section 5 discusses the implications of the findings.

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 sales of new successful products, as the diffusion curve in Fig. 1 shows, follow a typical S-shaped development: the diffusion starts slowly, after some time it takes off showing a strong increase in growth-rate, and finally it saturates when a certain level of marketing penetration has been reached (Rogers, 2003). At first, when a new product enters 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 take off. Then, when the product has reached a critical mass of market penetration, 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 product has penetrated the majority of the market. Finally sales decrease and then stabilize, whereas the growth rate stabilizes and then decreases. These are usually the empirical diffusion dynamics of successful market entries (Bass, 1969).

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; Lilien et al., 1981). However, the general approach of these works has 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). Hence, the questions why so many innovations are not successful and how promotions can help product sales to take off still require a great deal of explanation.

What makes the success of a new product so difficult to achieve? Why is it so unpredictable? Arts et al. (2006) conducted a meta-analysis of the innovation diffusion field, showing that many studies report a multitude of explanatory

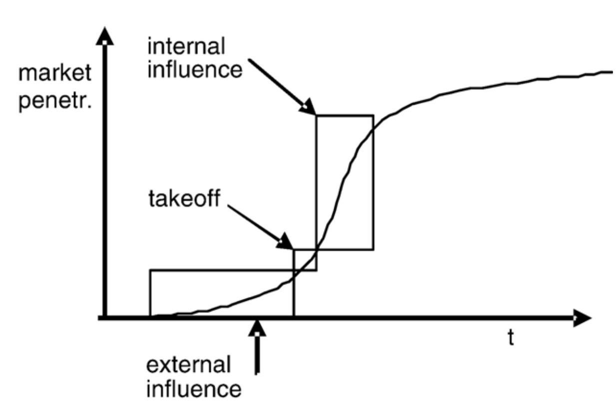

Fig. 1. The S-shaped curve of the diffusion.

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., 2001a,b), 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. Social influences dominate markets, 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 a combination of a small number of favorable events convinces 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 breakthrough 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 paper 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 is twofold: when launching a new product a sharp trade-off exists between the two extremes of the promotional strategies. First, the promotion strategy can be like *throwing rocks*, i.e. presenting the product to one or a 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 neighbors 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 takeoff highly varies for different kinds of durable categories (Golder and Tellis, 2004). Golder and Tellis (2004) find that entertainment and information goods (brown goods) take off four times faster than durables, such as kitchens 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 (Sawhney and Eliashberg, 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 offers the consumers (Tellis et al., 2003). Market penetration at the time of takeoff varies from 3% to 16% (Rogers, 2003). This paper adopts a standard operational measurement that identifies takeoffs depending on market penetration (Golder and Tellis, 1997; Tellis et al., 2004). 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.

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 in which they can communicate. Such networks can vary from completely regular ($r=0$) to completely random ($r=1$) (Watts and Strogatz, 1998). When the network is completely regular, agents are highly clustered and the information takes a 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, spreads 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, whereas the information spreads very fast to all the clusters of the network. This paper adopts a slightly different variation of the Strogatz and Watts model, having a regular lattice and added random links. These random links present a low percentage of the total number of links ($0.01 \leq r \leq 0.1$). This version of the model maintains the same properties of the Small-World area (Newman, 2002; Newman and Watts, 1999). Many works describe how diseases and knowledge spread through Small-World networks (Cowan and Jonard, 2004; Newman, 2002; Newman and Watts, 1999). Delre et al. (2006) propose how to adapt these models of diffusion to social and economic contexts. Because the authors do not focus on how network structures affect diffusion patterns, this paper adopts a single fixed network structure, which can more generally represent the connections among the consumers (for the values of the parameters see Appendix A).

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The agent decides whether or not to adopt the product and, if so, he/she communicates this to the other agents linked to him/her. 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 agent i obtains when consuming product j is higher than the minimum level of utility that agent i requires:

$$U_{i,j} \geq U_{i,j,\mathrm{MIN}} \tag{1}$$

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

$$U_{ij} = \beta_{i,j} \cdot x_{i,j} + (1 - \beta_{i,j}) \cdot y_{i,j} \tag{2}$$

where

$$y_{i,j} = \begin{cases} q_j \geq p_i \Rightarrow 1 \\ \text{otherwise} \Rightarrow 0 \end{cases} \tag{3}$$

$$x_{i,j} = \begin{cases} a_i \geq h_{i,j} \Rightarrow 1 \\ \text{otherwise} \Rightarrow 0 \end{cases} \tag{4}$$

$$a_i = \frac{\text{adopters}_i}{\text{adopters}_i + \text{non} - \text{adopters}_i} \tag{5}$$

$U_{i,j,\mathrm{MIN}}$ specifies i's minimum utility requirement and $U_{i,j}$ is the utility of agent i, when he/she 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_i 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 his/her neighbors' behavior, 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 he/she does not. (For an analysis of how personal networks affect diffusion dynamics, see Delre et al., 2006). 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 him/her 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 an agent has adopted the product, at the following time step, other agents connected to him/her also get involved in the WOM process. Then, they too evaluate their utility according to Eq. (1) and decide whether or not to adopt the product. In this way the process of diffusion spreads out through the whole network of consumers. If this wave of adoption stops at a certain time, one may conclude 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 the campaigners organize a new external promotion. This launch framework serves for analyzing how different promotion strategies, such as targeting, affect the final marketing penetration (Section 4.1).

A second way of launching a product is by mass media campaigns. This study simulates mass media campaigns, allowing all agents to be involved in the decision-making rule (1) with probability e_2. The authors use this launch framework when analyzing how the timing of the promotional mass media campaigns dynamically affects the diffusion (Section 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, the agents decide whether or not to adopt a product only after becoming aware of the product. They 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 the decision-making process 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 traveling 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 (Van den Bulte and Stremersch, 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 kitchens and laundry machines (with $\beta_{i,j}$ varying from $N\sim(0.75, 0.01)$ to $N\sim(0.8, 0.01)$ and

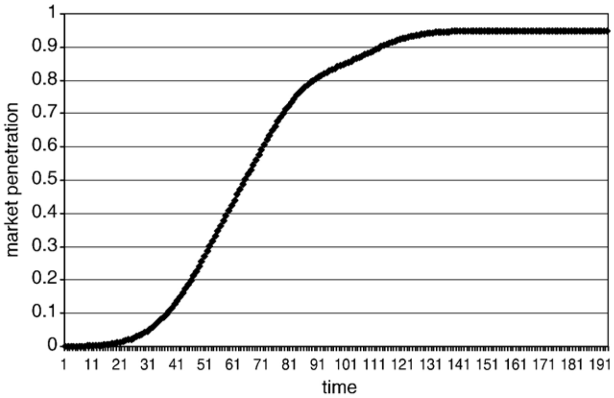

Fig. 2. The market penetration v_t at each time step.

$h_{i,j}$ varying from $N\sim(0.35, 0.01)$ to $N\sim(0.4, 0.01)$) and brown good markets, such as TVs, CDs, and 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 the authors have made some assumptions. The Appendix specifies the complete list of the parameters, their values and the underlying theoretical assumptions.

In order to precisely identify a takeoff and its time, the authors 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. Fig. 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 $e_2=0.001$). The new product takes off somewhere between time step 30 and time step 40. Based on a visual threshold chosen ad hoc, 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:

$$g_t = (S_t - S_{t-1})/S_t \tag{5}$$

$$v_t = S_t/N \tag{6}$$

$$T_t = (1-v_t)^{\gamma} \tag{7}$$

Parameter γ shapes the takeoff threshold and, following Golder and Tellis (1997) and Tellis et al. (2003), the authors select γ to make the best prediction visually. Fig. 3 shows an example. The first time that 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: $S_t=\sum_{i=5} s_{t-1}$.

Moreover, in order to avoid the risk of taking minor absolute growths for takeoffs because they resemble high relative growths, the authors only collect takeoffs 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, the authors 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. Fig. 3 permits us to identify precisely that the time to take off is 40 time steps.

4. Simulation experiments and results

First, the authors investigated the different kinds of launches that varied with the dimension and the targeting of the promotion. Second, they explored issues regarding the right timing of the post-launch mass media promotional campaigns. These issues provide insights into the optimal timing with respect to the different product categories in the different markets.

4.1. Targeting strategy: throwing rocks versus throwing gravel

These simulations explore the diffusion patterns in a market where the decision of each consumer highly depends on what other consumers do ($\beta_{i,j}=N\sim(0.8, 0.01)$ and $h_{i,j}=N\sim(0.35, 0.01)$). 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 that randomly assign a product to a number of consumers. In this way, the researchers assessed how big the targeting promotion has to be in order to ignite the social contagious process. At the end of a simulation, all the 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 the authors varied e_1 at the beginning of the simulations and they collected the values of the market penetration v_t at the end of the simulation runs. Fig. 4 shows

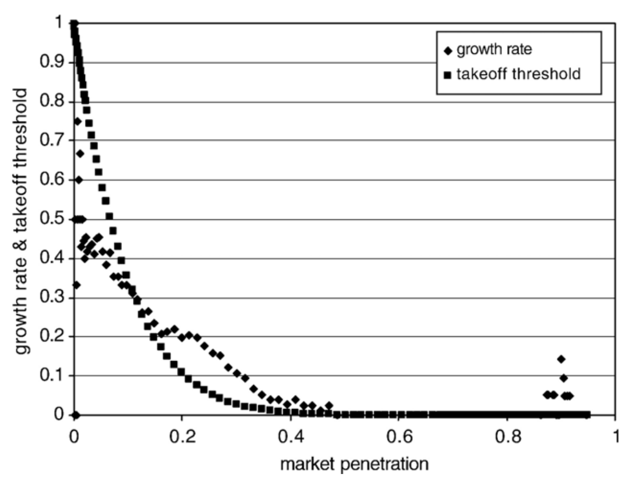

Fig. 3. The growth rate g_t plotted against the market penetration v_t and the threshold for the takeoff identification.

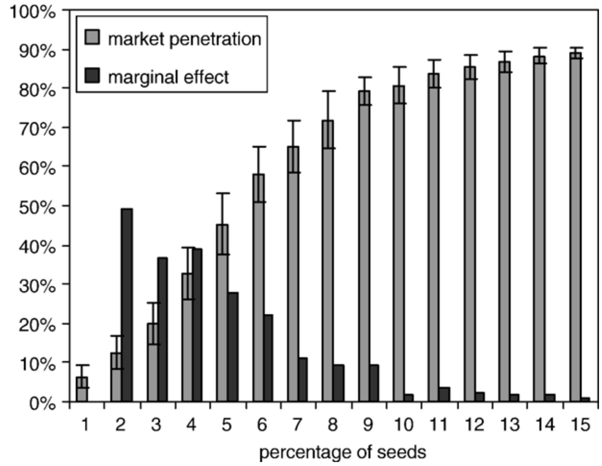

Fig. 4. Market penetration v_t and marginal effect varying with the number of seeds at moment of launch.

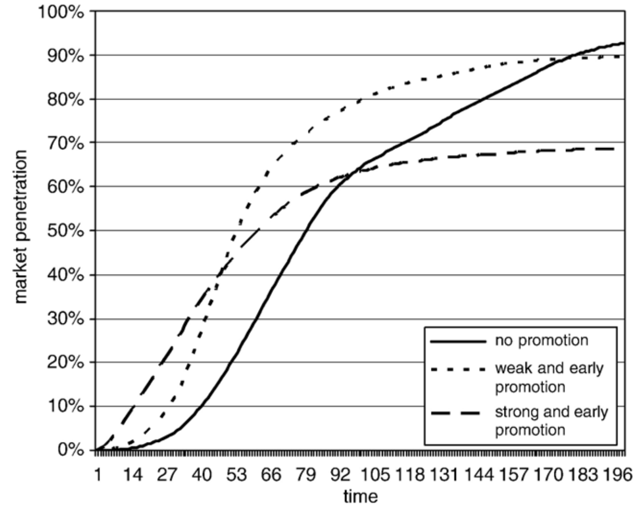

Fig. 6. Diffusion curves for different mass media campaigns (strong $e_2=0.05$ and weak $e_2=0.005$) placed at the beginning of the diffusion (from time step 0 until time step 10).

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 successful final market penetration. However, such a strategy is unrealistic because of the high costs involved; managers should therefore decide to plan alternative targeting strategies.

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 neighbors 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 subjecting part of the seeds to the throwing gravel strategy and the other part to the throwing rock strategy. This method facilitates the diffusion

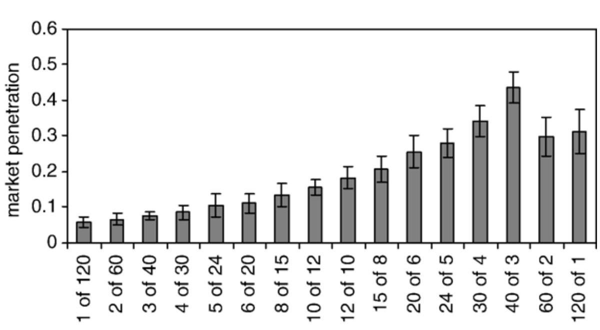

Fig. 5. The market penetration v_t at the end of each simulation run balancing the throwing gravel strategy and throwing rocks strategy.

of a new product by spreading both the product 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 centers of adoption in different places of the market that hopefully ignite the diffusion desired throughout the entire market. The model can be used to ascertain the desired number and size of these groups. Fig. 5 shows what happens when distributing the same number of seeds ($e_1=0.04$) but in groups of different sizes. The outcomes are very different and the best strategy, as already mentioned, is to find the right balance between the two extremes. In this case (with 3000 agents and 120 seeds, $\beta_{i,j}=N\sim(0.8\ 0.01)$ and $h_{i,j}=N\sim(0.35,\ 0.01)$), the best strategy consists of focusing on 40 groups, each one with 3 consumers.

This result is robust for a wide range of parameters. When the authors set the parameter values in such a way that the market penetration at the end of the simulation moves 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_1 varying from 3% to 5%), they obtain similar outputs. Moreover, when they 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 the market penetration is lower, the best targeting strategy tends to be one that aims at fewer but bigger groups.

Finally, Fig. 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.

4.2. 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 by positioning seeds at the moment of launch and increasing the strength of mass media messages during the post launch. In this

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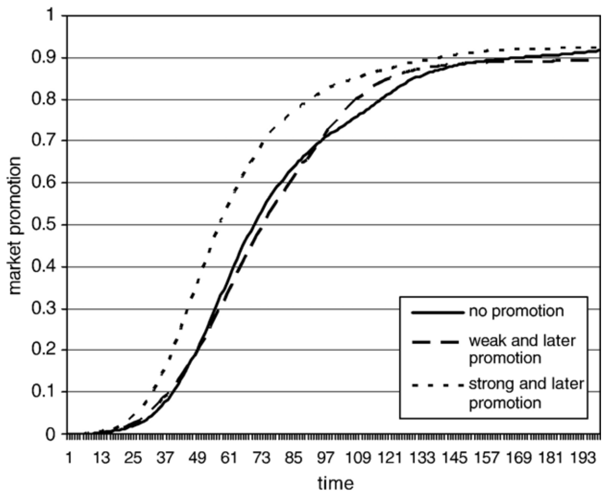

Fig. 7. Diffusion curves for different mass media campaigns (strong $e_2 = 0.008$ and weak $e_2 = 0.002$) placed at a later stage of the diffusion (from time step 20 until time step 50).

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 one can explain innovation diffusions by marketing effort rather than by social contagion (Van den Bulte and Lilien, 2001) and that one can start from a consumer's heterogeneity in order to generate S-shaped adoption curves (Chatterjee and Eliashberg, 1990).

The simulation model used allows one 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. Figs. 6 and 7 show the results of early and later mass media campaigns, respectively. In order to simulate mass media promotional campaigns, the authors changed the value 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, the authors set $e_2 = 0.001$ at the initiation of the diffusion. Then, from time step 0 until time step 10, they simulated the mass media campaign under two circumstances: $e_2 = 0.005$ (weak campaign) and $e_2 = 0.05$ (strong campaign). For these simulation runs the authors set the model to $\beta_{i,j} = N \sim (0.9, 0.01)$ and $h_{i,j} = N \sim (0.4, 0.01)$. The results (Fig. 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, if the promoters advertise the product too soon and too strongly, the diffusion does take off but realizes 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, deciding not to adopt the product because not enough other consumer have done so yet. Then, many groups of consumers that have decided not to adopt the product at the beginning of the diffusion, may exert a negative social influence as a result of which the market penetration remains low. On the other hand, if the mass media campaign is not so strong, the diffusion is positively supported and thereby it takes off faster. In this way, the process will hardly lose out in terms of marketing penetration. Fig. 7 shows the opposite situation. The diffusion starts with $e_2 = 0.001$ and then, from time step 20 until time step 50, $e_2 = 0.002$ (weak campaign) or $e_2 = 0.005$ (strong campaign) simulate a later mass media campaign. One can see clearly that, compared with the absence of extra mass media promotional campaigns, the weak campaign does not bring substantial advantages to the diffusion curve. On the other hand, the strong campaign helps the growth phase of the diffusion curve. 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.

4.3. Different markets: white goods versus 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. On the other hand, 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 this distinction between product categories by varying the $\beta_{i,j}$ and $h_{i,j}$ parameters in the individual decision-making process of the agents. When $\beta_{i,j}$ is high and $h_{i,j}$ is low, this results in brown good markets. The individual decision-making highly depends on what neighbors decide to do, and even if just a few neighbors adopt the product, the agents perceive

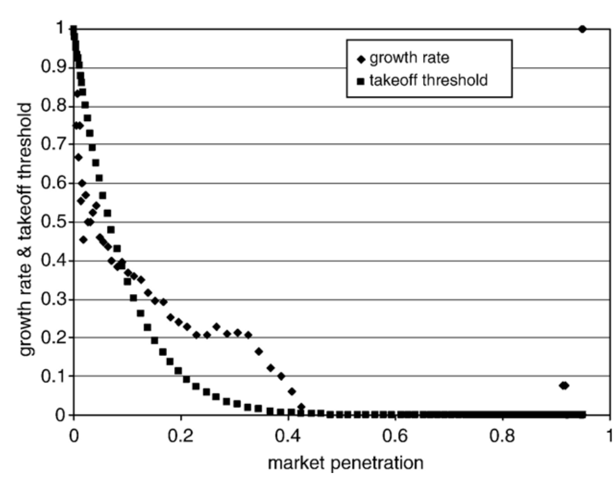

Fig. 8. Takeoff identification for brown goods.

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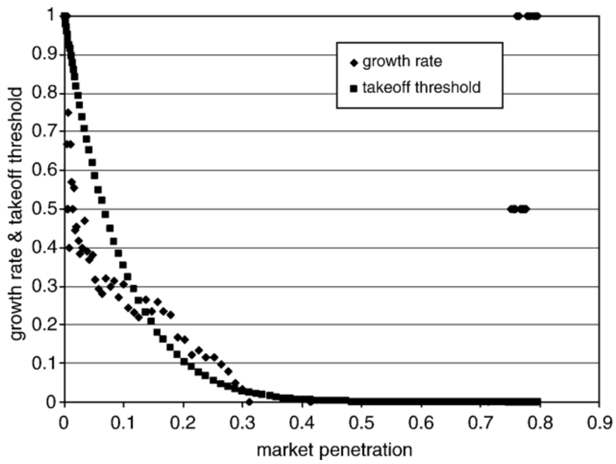

Fig. 9. Takeoff identification for white goods.

social influence. At this stage the agents are very susceptible and the market becomes fashionable. A low $\beta_{i,j}$ in combination with an increasing $h_{i,j}$ simulates white good markets. Because the individual preferences weigh more heavily in the individual decision of the agents and more neighbors have to adopt the product for an agent to perceive social influence, such a market becomes less susceptible to contagious processes. The authors have conducted simulation experiments for the two categories and identified takeoffs from the simulated diffusion curves. Figs. 8 and 9 show the growth rate curves of brown and white 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 the Appendix. It is clear that brown goods (v_t=0.101) take off more quickly than white goods (v_t=0.136).

The authors varied 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, they increased the value of e_2 (from e_2=0.001 to e_2=0.05) for a given period of time (10 time steps) to determine the effect on the diffusion curve of this extra campaign when taking place at different times during the diffusion. Tables 1 and 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.

Table 1
Takeoff identification for white goods with different timings of the same mass media campaign

	Takeoff	$g(t)$	$v(t)$	t	Final market penetration
No prom	Yes	0.18	0.175	40	0.772
Prom 10–20	Yes	0.892	0.031	12	0.671
Prom 20–30	Yes	0.552	0.064	23	0.641
Prom 30–40	Yes	0.576	0.064	33	0.568
Prom 40–50	Yes	0.3	0.117	31	0.665
Prom 50–60	Yes	0.372	0.113	33	0.755

Table 2
Takeoff identification for brown goods with different timings of the same mass media campaign

	Takeoff	$g(t)$	$v(t)$	t	Final market penetration
No prom	Yes	0.396	0.112	27	0.951
Prom 10–20	Yes	0.923	0.028	13	0.95
Prom 20–30	Yes	0.469	0.085	20	0.952
Prom 30–40	Yes	0.437	0.085	26	0.947
Prom 40–50	Yes	0.488	0.086	28	0.951
Prom 50–60	Yes	0.333	0.113	28	0.95

The timing of the promotional activity is crucial for both product categories. Under the given conditions, the takeoff of white goods enhances when the extra mass media promotional campaigns take place at any time before the takeoff. In fact, when the extra campaign takes place between the launch and the takeoff (in the case of no extra campaigns the promotion occurs at time step 40 and at market penetration v_t=0.175) the diffusion always enhances, both in terms of timing and in terms of market penetration. In addition, the growth rate g_t increases consistently. However, the results show (see also Section 4.2) that extra mass media campaigns at this early stage of the diffusion have a negative effect on the final market penetration. This negative effect can amount to up to 20% of the potential market: the final market penetration is 0.772 with no extra campaign and 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 simulating brown good markets, the authors always observed a faster takeoff when a promotional activity of the same strength took place. With respect to the no extra promotional campaign, the different timings of the same mass media promotional campaign anticipated 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 occurred at time step 27 and at v_t=0.112 and could be anticipated until time step 13 and v_t=0.03 without any negative effects on the final market penetration.

The authors can summarize these results by pointing out that one can always enhance the takeoff of new products in both brown good markets and white good markets. However, in terms of final market penetration, it is much riskier for white good markets. With respect to brown good markets, mass media promotional campaigns are more efficient when they take place just after the launch. In this way, they have the effect of anticipating the takeoff point without losing any potential market.

5. Conclusion and discussion

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, spreading through networks of consumers. Promotion strategies are meant to be the sparks that start the fire. This 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 takeoff 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 center of consumption that is highly visible to other consumers, and the throwing gravel strategy, which creates as many centers of consumption as possible in each area 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 such a case, many consumers decide not to adopt the product because not enough others have done so yet, which hampers the diffusion. On the other hand, 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, which has demonstrated that non-price determinants have a strong impact on the takeoff of new products (Agarwal and Bayus, 2002; Goldenberg et al., 2001a). Whereas these works focus more on the supply side of the innovation, this 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 messages suggest that in white goods markets campaigns can anticipate the takeoff time but are also very dangerous because they risk hampering the final diffusion. The authors advise to start a strong mass media campaign only if at least 10% of the market potential has already adopted the product. In the brown goods 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 a large number of critical assumptions have to be made (see Appendix A). A fruitful and promising venue of research consists of calibrating agent-based models by using laboratory experiments and surveys (Janssen and Ostrom, in press). In this way the extant assumptions become less restrictive because the empirical evidence supports them. So agent-based models may also become promising predictive tools. As such they may contribute to the normative validation of the innovation diffusion methods and, more generally, to the analysis of social and economic phenomena.

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Appendix A

Name	Parameter	Values	Theoretical assumptions
Simulation runs		20	In order to make our results more robust, the authors ran 20 simulation runs per each condition. They report the average and, when necessary, the standard deviation of the different runs.
Time steps of the simulation run		500	In all simulation runs, the system converged to a steady state where no more adoptions were observed.
Number of agents	N	3000	None
Number of shortcuts into the network	R	0.01	The global network structure is a Small World. Consumers are very clustered but information can travel fast through the network.
Minimum level of satisfaction of the agent i	$U_{i,\mathrm{MIN}}$	Uniform distribution [0, 1]	None
Personal preference of the agent i	p_i	Uniform distribution [0, 1]	None
Quality of the product j	q_j	0.5	The product characteristics are neutral to consumers' preferences. The likelihood that a given consumer likes the product is the same as the likelihood that he/she does not like the product.
Takeoff threshold identification	Γ	Form 8 until 12 Default value: 10	The takeoff threshold decreased exponentially with marketing penetration. The more the marketing penetration, the more the decrease in the chances of observing a takeoff. Similar results were obtained with γ varying from 8 t 12.
Proportion of seeds (targeted consumers)	e_1	Independent variable	None

(continued on next page)

Appendix A (*continued*)

Name	Parameter	Values	Theoretical assumptions
Probability of messages of mass media campaigns to reach a consumer	e_2	Independent variable Default value: 0.001 Strong mass media campaign: from 0.005 until 0.05 Weak mass media campaign: from 0.0005 until 0.002	None
Personal threshold sensibility to neighbors influence	$h_{i,j}$	Independent variable Default values for brown goods: $N \sim (0.3, 0.01)$; default values for white goods: $N \sim (0.4, 0.01)$	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 (Granovetter and Soong, 1986; Alkemade and Castaldi, 2005).
Weight of individual part and social part of an agent i in the utility function	$\beta_{i,j}$	Independent variable Default values for brown goods: $N \sim (0.1, 0.01)$; default values for white goods: $N \sim (0.25, 0.01)$	Consumers' decision-making depends for the greater part on what other consumers do (internal influence). Consequently, social contagion is the main driver of the diffusion curves in general and the growth stages in particular (Bass, 1969; Mahajan et al., 1995). The internal influence is stronger for brown goods than for white goods (Tellis et al., 2003).

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