# Effects of social networks on innovation diffusion and market dynamics

Delre, S.A.

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# The Effects of Social Networks on Innovation Diffusion and Market Dynamics

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# Preface

In this preface I would like to thank those that have supported me during my PhD project. I would first like to thank my Italian professors Dominico Parisi, Roberto Cordeschi, and Marcello Frixione who have encouraged me to do my PhD abroad.

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I am very much indebted to Thijs Broekhuizen. He made me become a fond of marketing suggesting me always very interesting articles to read and having exciting endless discussions about how people behave and how societies work.

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Sebastiano Alessio Delre
Groningen, July 2007.

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# 1 Introduction

## 1.1 Purpose of the study

In the last ten years the academic interest on natural and artificial networks has enormously increased. The first article that ignited this explosion appeared on the 4th of June 1998 in *Nature* and its title is *Collective dynamics of 'small-world' networks* (Watts and Strogatz, 1998). In this paper, Watts and Strogatz show that many different networks, both natural (e.g. the neural network of the worm Caenorhabditis elegans) and artificial (e.g. the power grid of the western United States and the collaboration graph of film actors), display two characteristics: the nodes of the networks are highly clustered (if node A is connected to node B and node A is connected to node C, then it is very likely that also B and C are connected) and the average shortest path between two nodes is very low (going from node A to node B passing by other nodes takes just a few steps). The authors propose a very simple model in order to formalize a continuum between a regular network and a random network, they define the small-world area as that area of the network that displays those two characteristics and they identify it in the networks mentioned above.

The literature about network structures was already quite developed, especially in social science (Burt, 1992; Milgram, 1967; Wasserman and Faust, 1995; for a useful overview the reader can visit the International Network of Social Network Analysis (INSNA) web page: http://www.insna.org). But the great merit of Watts and Strogatz's paper was that, besides attracting many other scholars from different fields of the academic world (Amaral et al. 2000; Barabasi and Albert, 1999; Newman, 2002; Pastor-Satorras and Vespignani, 2002; Young, 2002), it also created the basis for a huge interest from a general public (Barabasi, 2002; Watts, 2004). In our opinion, this new big wave of interest on networks had two main causes. First, network structures explain complex phenomena with very simple models and test them with interesting data sets.

Second, but equally important, it allows researchers to formalize very large networks. While the previous existing literature focused on the interesting dynamics of social networks that formalized small groups of friends and/or small organizations, this new network fashion of the academic world makes use of large networks with several thousands of nodes. Consequently, the number of phenomena to which these new network models can be applied dramatically increases. In less than ten years the number of publications about network structures literally exploded. These works flourished in the field of statistical physics (e.g. Amaral et al. 2000; Barrat et al. 2004) but almost immediately they invaded other fields such as computer science (e.g. Albert et al. 2000), biology (e.g. Dodds and Watts, 2005), epidemiology (e.g. Newman, 2002) and again social science (e.g. Deffuant et al. 2005).

In economics there is no large stream of research on this topic though some interesting and authoritative publications appeared also in the field of economics using these new network models (Gaber et al. 2004; Janssen and Jager, 2001; Young, 2002). The main goal of this thesis is: *to adapt network models to a marketing framework that includes consumers' preferences and social influences among consumers and to apply these models to study their effects on innovation diffusion and market dynamics*.

First, we study how the penetration and the speed of the diffusion of a new product that enters different markets are affected by different global network structures (scale-free network and small world network) and by local network specifications (cost constraints for number of links, weighted links, directed links and small versus large personal networks). Second, we focus on the effects of local network characteristics: simulating different levels of consumers' heterogeneity concerning the individual susceptibility to the others' behaviours and different specifications of the influence that the hubs of the network have on other consumers, we test the variations on the speed, the degree and the uncertainty of the market penetration. Finally, we direct our study towards marketing strategies (i.e. different targeting and different timing of promotional campaigns) and we show how some of these strategies result in an enhancement of the final penetrations for different categories of new products.

## 1.2 Innovation diffusion

In Western societies the concepts of development and innovation are closely related and the recent acceleration of technological change of the modern societies has further strengthened this link. It is possible to define development as consisting of a change and the diffusion of this change (Adner and Levinthal, 2001; Utterback and Abernathy, 1975). The field of marketing has mainly focused on the latter and it has acquired a substantial body on knowledge about it. Here, the diffusion process has often been associated with the diffusion of new products, it has been addressed as innovation diffusion and it has been widely studied using field data (for a review, see Arts et al. 2006; Mahajan et al. 2000; Ruiz, 2005; Meade and Islam, 2006).

The roots of this stream of research reside in the works of Bass (1969) and Rogers (1995). The Bass model formalizes the innovation diffusion process by means of a simple differential equation (3.1). The parameters of this model refer to two different kinds of adoption: adoption caused by external influence (e.g. advertising) and adoption caused by internal influence (e.g. word-of-mouth (WOM) and imitation). After the work of Bass, many new product diffusion models have appeared in the marketing field trying to include the effects of other relevant variables that affect the innovation diffusion process. Ruiz (2005) presents a complete review of the new product diffusion models that followed the original work of Bass. For example, many studies have advanced the sophistication of this kind of models including multi-stage diffusion models that allow considering heterogeneous populations (Jain et al. 1991; Hahn et al. 1994), dynamic potential market (Bass et al. 1994; Jain and Rao, 1990), dynamic internal and external influences (Jain et al. 1995; Lilien et al. 1981; Parker, 1993; Hahn et al. 1994; Parker and Gatignon, 1994), repeated purchases (Lilien et al. 1981), competition (Krishnan et al. 2000; Parker and Gatignon, 1994), and so forth.

These models formalize the diffusion at the aggregate level, which basically means that the sales of a new product are described, explained and forecasted according to macro variables (such as advertising, WOM, price, competition) that describe the market as a single entity. However, they exclude the micro level variables that affect the individual adoption of the consumers. In the marketing literature the studies about micro-level drivers of adoption have formed an independent and separated line of research. This research focused on how consumers' attitudes and behaviour are affected by product characteristics such as relative advantage, compatibility, complexity, trialability and observability (for a review see Arts et al. 2006).

Besides the particular results described in the chapters that deal with innovation diffusion (chapters 2, 3 and 4), our main contribution to the literature of innovation diffusion is building a bridge between these two streams of research.

## 1.3 The cinema market

The idea that the global and local structures of the consumers' relations affect the way consumers behave and consequently the aggregate dynamics of the market is based on the fact that the human decision making highly depends on what other people do (Granovetter, 1978; Veblen, 1899). In marketing and micro economics this idea has a long tradition (Granovetter and Soong, 1986; Katz and Lazarsfeld, 1955) and it has been referred to as social influence (Batra et al. 2001; Bearden et al. 1989; Jager, 2000; Mangleburg et al. 2004; Terry and Hogg, 1996). The effects of social influence usually cause a convergence of the decisions of the consumers (Banerjee, 1992; Bikhchandani et al. 1998; Rosen, 2000). Take the cinema market, for example. Here, the decision making of the movie goers is highly interdependent and often this market is considered as a typical example of a winner-take-all market (De Vany, 2004). In this kind of markets a few successful products usually obtain high market shares and the rest of the products have to make up with very low shares (Frank and Cook, 1995). Social influences can determine the convergence of consumers. Salganik et al. (2006) showed that the inequalities of the market outcomes are significantly higher in the social influence condition compared to the independent condition.

Chapter 5 deals explicitly with the issue of social influence. It focuses on the cinema market, it proposes an agent based model that formalizes the decision making of the movie goers and it explains why the box offices of the movies are very unequally distributed and why the typical life cycles of the most successful movies almost always display the same fast decay.

The motion picture industry has recently attracted the attention of many scholars in the field of marketing (for a complete review see Eliashberg et al. 2006).

Basically this is due to the high visibility that such a market has on a large audience and because the data about the characteristics of this market are very easy to obtain. The revenues that movies gain at the box office are published every week and are available from different sources (see for example http://www.variety.com, http://www.the-numbers.com, http://www.imdb.com). Also the production and the marketing budgets that the large studio producers or the independent producers spend in order to produce, advertise and distribute the movies are often public, especially for the most visited movies. Finally, this industry displays some specific characteristics that call for explanation. One of these resembles a paradox: a large majority of the movies produced result in a loss. Why do movie makers keep on producing movies if they know that it is quite likely that their movies will encounter a loss? Such incongruence reflects the well known uncertainty that governs this market. At the moment of the opening weekend, when a new movie enters the cinema theatres, it is very difficult to predict how many visitors the movie will have attracted to the cinema theatres at the end of its life cycle (De Vany, 2004; De Vany and Walls, 1999). This characteristic of the market is partially explained when considering the high inequalities observed at the box office. The cinema market is a typical example of a winner-take-all market where a few movies become big hits and obtain a great part of the market shares while the remaining movies have to be content with small market shares (Elberse and Oberholzer-Gee, 2006; Frank and Cook, 1995). If we sum up all the profits of the cinema market we will certainly obtain a large positive number. This is due to the facts that the biggest hits of the market are just a few movies which generate large profits, whereas a majority of movies generate financial losses.

Our decision of focusing on the motion picture industry was certainly facilitated by all the reasons mentioned above, but the main reason is that the cinema represents a market where social influences are dominant, and we believe that a significant part of the described odd characteristics are caused by them. In chapters 5 we present a simulation model that is based on the demand of the market and that is aimed at explaining how the social influences, that affect the decision making of the movie goers, cause the large differences in the market shares that we observe in this industry.

## 1.4 The methodology: computational models and simulations

In economics, the idea that market outcomes can be explained as a result of many individual decisions is widely accepted. However, the micro studies on the individual behaviour of economic agents and the macro studies on aggregate market variables resulting from the individual behaviour have almost always been separated. In the marketing field, for example, the works on the effects of marketing efforts on aggregate variables like sales and the works on consumer behaviour are quite distant to each other and are often considered as two separated fields. Traditionally in economics the micro and macro levels have maintained a certain distance because often, almost always, the summation or the extrapolation of the aggregate from the individual behaviours is not trivial. In order to make a connection between micro and macro it is necessary to understand the influences that people exert on each other, and this is usually not easy. (Coleman, 1987; Schelling, 1978; Young, 2001). To have an idea of how unexpected the aggregate outcomes may be we may mention several examples. It can happen that different individuals become completely segregated in similar groups although their preferences are not particularly in favour of similar individuals (Schelling, 1978). It can happen that every week the large majority of movie goers direct their visits to two or three movies even if their individual preferences are widely spread to the dozens of movies that enter the cinema theatres (De Vany, 2004).

In economics, computational models may furnish a great help in studying and explaining the connections between the micro and the macro levels. Computational models are models expressed as algorithms and implemented as software. They simulate a set of processes observed in the world in order to understand better these processes. They aim at studying, explaining and predicting the outcomes of these processes given a specific set of input parameters. The accelerating growth rate of computational power of the last decades has permitted the flourishing of different kind of computational models (Simon, 2001). In particular, in the last 20 years the agent based computational economics has become a widely recognized methodology that contributes to the classical topics investigated in different fields of economics. Agent based models are computational models consisting of independent interacting agents (Shoham, 1993). In economics, they simulate economic entities such as consumers, producers, families, firms, institutions, etc. For a complete and detailed overview of how this methodology has been applied in economics, the reader is refereed to Tesfatsion and Judd (2006).

Considering the recent tremendous growth of the use of computational models, it is very likely that in the future their use will still grow considerably. We maintain the idea that academic research in economics may find a new enhancement if it makes a profitable use of the opportunities that computational models offer (Flache and Macy, 2005; Hegselmann and Flache, 1998; Garcia, 2005; Gilbert and Troitzsch, 1999; Goldenberg et al. 2004; Lusch and Tay, 2004; Tesfatsion and Judd, 2006). In particular, we believe that the use of computational models may contribute in filling the gap between micro and macro levels. The work presented in this thesis is thoroughly grounded on the methodology of agent based models. In fact each chapter addresses a different marketing question and it proposes a different agent based model to answer it. However, this work of this thesis embarks also on an attempt to integrate these agent based models with empirical support. In chapter 5 we test the simulation outcomes of the agent based model against empirical data at the macro level of the market.

Figure 1.1 illustrates a methodological process in order to guarantee empirical support to computational models and it represents the relation between the agent based models proposed in the chapters of this thesis and the empirical phenomena they try to explain. It is a cycle that involves two levels of analysis: micro and macro. It suggests computational models like our agent based models, that aim at explaining economic phenomena, to conduct two empirical tests: one, called calibration, for the assumptions made at the micro level (agent decision making, relations among agents and relations between the agents and the environment) and an other one, called validation, for the simulation results obtained (market outcomes like penetration of a new product, market inequalities, etc.).

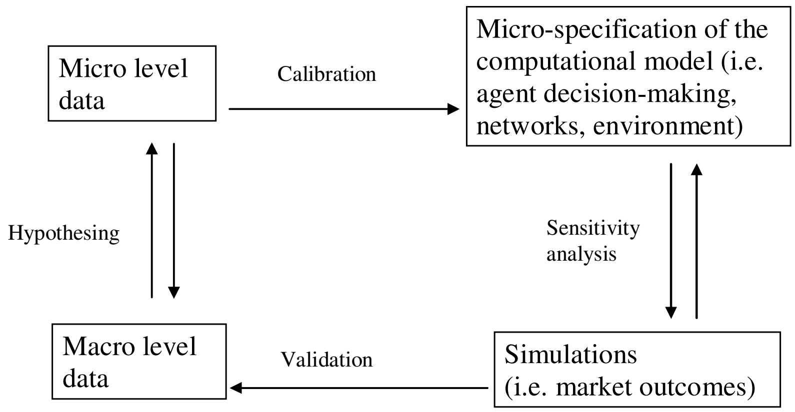



*Figure 1.1. The cycle for the empirical support of our agent based models.*

## 1.5 Contributions and outline of the dissertation

The work of this thesis contributes to the marketing literature enhancing theoretical and practical knowledge about how social processes affect the micro decision making of the consumers and what the resulting effects on the macro dynamics of the market are. It proposes models that are inspired by the consumat approach (Jager, 2000; Jager and Janssen, 2003). This approach revisits the needs that drive the consumer behaviour at the micro level and it suggests to use social simulation models (Gilbert and Troitzsch, 1999) in order to derive the resulting marketing outcomes at the macro levels. Examples of implementing the consumat approach for explaining different economic phenomena are Janssen and Jager (1999); Janssen and Jager (2001); Janssen and Jager (2002); Janssen and Jager (2003). As mentioned in section 1.2 and section 1.3, the proposed models of this thesis are directed towards two well known marketing topics. The first one is a traditional transversal topic that involves many industries: innovation diffusion; the second one is a particular industry that recently has become the object of analysis in the field of marketing studies: the motion picture industry.

About the former, chapter 2 and chapter 3 show how market dynamics can vary for different network structures that represent the relations of the consumers. Here we show which network structures help the diffusion of a new product and which ones do not; we show how social influence dampens the diffusion at the beginning of the life cycle and enhances it at the end of the life cycle. In chapter 4 we show how optimal targeting and timing strategies of promotions result in higher market penetrations for different product categories. About the latter, chapter 5 presents a model that simulates the USA motion picture market. It generates movie life cycles that are highly similar to the real ones and it shows how social influences create market inequalities at the box office. Finally, in chapter 6 we summarize the main conclusions of this work and we discuss further venues of research.

# 2 Will it spread or not? The effects of social influences and network topology on innovation diffusion[1]

Innovation diffusion theory suggests that consumers differ concerning the number of contacts they have, the degree and the direction to which social influences determine their choice to adopt. To test the impacts of these factors on innovation diffusion, in particular the occurrence of hits and flops, we introduce a new agent based model for innovation diffusion. We depart from existing percolation models by using more realistic agents (both individual preferences and social influence) and more realistic networks (scale-free with cost constraints). Furthermore, we allow consumers to weight the links they have and we allow links to be directional. In this way we model the effect of VIPs who can have a relatively large impact on many consumers. Results indicate that markets with high social influence are more uncertain concerning the final success of the innovation and that it is more difficult for the innovation to take-off. In addition, we show under what conditions highly connected agents (VIPs) determine the final diffusion of the innovation.

## 2.1 Introduction

The dispersion of new products, practices and ideas in a population is the basic process underlying societal change. To understand these processes, many researchers have studied factors that determine the speed and the degree with which new products, practices and ideas propagate through a society (Rogers, 1995). This process is

[1] The work of this chapter is based on Delre et al. (2004) and on Delre et al. (2007c).

addressed as *innovation diffusion* and has been widely studied using field data (for a review, see Arts et al. 2006; Mahajan et al. 2000 and Meade and Islam, 2006). From the marketing perspective it is of great importance to understand how information starting from mass media (external influence) and travelling through word-of-mouth (WOM) (internal influence) affects the adoption decisions of consumers and consequently the diffusion of a new product.

Bass (1969) constitutes a fundamental contribution to the field of innovation diffusion by modelling this process at the aggregate market-level. Classical innovation diffusion models have mostly focused on aggregate variables like market penetration and advertising campaigns (Agarwal and Bayus, 2002; Golder and Tellis, 1997; Golder and Tellis, 2004; Mahajan et al. 1990a; Tellis et al. 2003). In this way, a line of research has been initiated that studies whether and how marketing mix strategies affect new product diffusions (Bass et al. 1994; Mahajan et al. 2000; Tellis et al. 2003). Another line of research has focused on the micro-level drivers of adoption by studying how consumer's attitudes and behaviours are affected by product characteristics such as relative advantage, compatibility, complexity, trialability and observability (Arts et al. 2006; Holak, 1988; Holak and Lehmann, 1990; Labay and Kinnear, 1981; Mahajan et al. 1990b; Mittal et al. 1999; Plouffe et al. 2001; Rogers, 1995). This stream of research contributed to our understanding of the micro-level factors that determine the adoption by individual consumers.

Despite the two research streams mentioned above, the effect of micro-level factors on the macro-level phenomena of diffusion processes remains largely unclear. It is very difficult to conduct controlled experiments on processes of innovation diffusion due to the lack of experimental control on many critical variables. Fortunately, simulation models (like cellular automata, agent based models, and percolation models) provide a tool to systematically conduct experiments on how micro-level variables affect the innovation diffusion process. An interesting line of research has been conducted in the field of statistical physics using *percolation models* (for an introduction see Stauffer, 1994). The basic idea is that there is a network of agents that have different states (e.g. buy or not buy). Percolation models formalize the rules that govern the changes of states of the agents at the micro-level and collect the resulting innovation diffusion at the macro-level. While some percolation models have appeared in marketing science (Gaber et al. 2004; Goldenberg et al. 2000; Goldenberg et al. 2001; Hohnisch et al. 2006; Libai et al. 2005; Mort, 1991; Solomon et al. 2000; Weisbuch and Stauffer, 2000), their use is still limited, especially compared to the field of statistical physics where the diffusion processes have been associated to social and artificial phenomena like epidemics and computer viruses (Dodds and Watts, 2005; Newman, 2002; Newman and Watts, 1999; Pastor-Satorras and Vespignani, 2002). Moreover, whereas simulation models provide a promising new venue in studying processes of innovation diffusion, those that have been applied in marketing have usually neglected important variables for the diffusion process. First, the network structures used in extant marketing literature are still very simple (regular lattice and/or small world network) and highly different from realistic consumer networks. Second, the decision-making of the economic agents is represented by only one or two parameters formalizing consumer preferences (Goldenberg et al. 2000; Hohnisch et al. 2006; Solomon et al. 2000; Weisbuch and Stauffer 2000). In particular, existing simulation models ignore social influences which may play a critical role in purchasing a product, e.g., in fashion markets consumers exchange not only product information, but also norms concerning consumptive behaviour (Cialdini and Goldstein, 2004). Next to individual preferences, these social norms affect the adoption decision of a consumer.

The use of simulation models can reduce the gap between the two mentioned research streams, permitting both the explicit micro formalization of how individual consumers decide and behave and the aggregation of these decisions at the macro-level of market penetration (Garcia, 2005). In this way, marketing modellers can study how WOM and social influences travel in a network of consumers, thus allowing for testing the effects of micro campaigns and marketing strategies on macro-level innovation diffusion.

The first goal of this chapter is to introduce a new agent based simulation model that integrates micro-level behaviours of consumers and macro-level innovation diffusion. The decision-making of the simulated agents is based both on individual preference compared to product quality and on social influence coming from neighbouring agents. The second goal of the chapter is to formalize different network structures that represent different market characteristics and to examine the effects of these market characteristics on the innovation diffusions.

Different markets imply different network structures of consumers (Bearden and Etzel, 1982; Bearden and Rose, 1990) and these structures may affect the final success of a new product that enters the market. With respect to the market characteristics, we first find that markets with high social influence are more uncertain concerning the final success of the innovation and that, on average, the new product has fewer chances to spread. Here, as consumers affect each other to adopt or not at the beginning of the diffusion, the new product has more difficulties to reach the critical mass that is necessary for the product to take off.

The second market characteristic we investigate is the role hubs have in the spreading of the innovation. A clear example is the Oprah Effect (Peck, 2002). In 1996 the Oprah Winfrey Show resuscitated the publishing industry launching the campaign “Get the country reading again”. Since the campaign began, the famous Oprah’s talk show generated 38 consecutive best selling books. In fashionable markets such as sport cloths, brands are often endorsed by famous persons. These VIPs are the hubs of the network because almost all consumers know them. It is a common marketing strategy to advertise a new product using VIPs because they guarantee an immediate visibility of the product. On the other hand, there are other markets where such VIPs do not exist. An example is the pharmaceutical market. The hubs of this market are the physicians that prescribe the medicine to their patients, but physicians have strong constraints to the number of patients they can have. Also here, a major part of the advertisement is directed to physicians because they have a dominant role in determining the success of the new medicine (Narayanan et al. 2004). Although hubs are present in almost any network of consumers, their roles and their effects in different markets can be very different. Using a scale-free network with a cut-off parameter for the maximum number of connections a hub can have (Amaral et al. 2000), we find that when hubs have limits to the maximum number of connections the innovation diffusion is severely hampered and it becomes much more uncertain. Our results also show that the strategic position of VIPs in the markets is very important for the diffusion because they make consumers aware of the new product. However, we find that their effect on the decision-making of the consumers can be often overestimated because they do not convince consumers to adopt more than what other normal friends do.

The chapter is structured as follows: in section 2.2 we briefly present what percolation is and how percolation models can be used to formalize diffusions; in section 2.3 we introduce our agent based model for innovation diffusion; in section 2.4 we present our simulation results and in section 2.5 we address the conclusions.

## 2.2 The Social Percolation Model

Here we shortly present the basic formalization of percolation models (Stauffer, 1994). The basic structure is a network of agents which usually takes the form of a regular lattice $\Gamma$ consisting of *LxL* cells. Each cell can be in only one of two possible states: not activated (0) and activated (1), and each cell is activated with probability *r*. Then, the fraction of activated cells will depend on the value of *r*. Figure 2.1 shows three possible situations with different *r* values. A cluster is defined as a group of activated neighbours and neighbours are defined as cells with one side in common. Percolation is defined to occur in $\Gamma$ when a cluster of cells is big enough to touch at least one cell of each row and each column of $\Gamma$. In Figure 2.1, we indicated the biggest clusters of activated neighbours. Percolation occurred only in the third case where $r$ = 0.60. A percolation threshold $r_c$ is defined as the minimum value of *r* for which we observe a percolation in $\Gamma$.

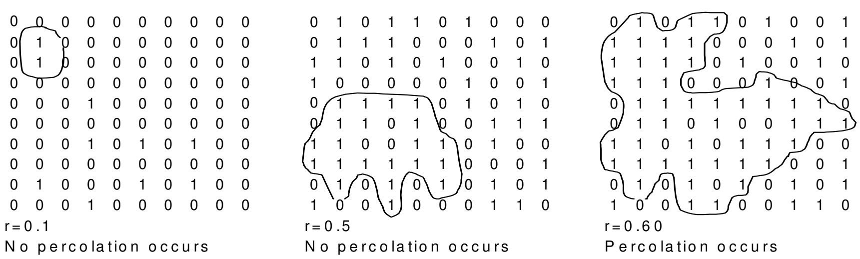



*Figure 2.1. Examples of percolation models in a lattice of 10x10 for different values of r.*

Solomon et al. (2000) and Weisbuch and Stauffer (2000) used percolation models to formalize hits and flops. In particular, they discussed the diffusion of WOM about a new movie that spreads through a population of agents. Their percolation model consists of a two dimensional square lattice where agents are situated in the cells. The agents are heterogeneous concerning their individual preference ($p_i$). In this regular lattice a few agents have already seen the movie and inform their four adjacent neighbours about the quality of the movie ($q$). When an agent $i$ is informed about the movie by a neighbour, it evaluates the movie and decides to see the movie if the quality is above the individual preference threshold ($q > p_i$). In the next time-step, if agent $i$ has seen the movie, the agent functions as a source of information reporting to its neighbours about the quality of the movie. If the movie quality is lower than the agent's preference ($q < p_i$), agent $i$ does not visit the movie and it does not inform its neighbours. If the individual preferences of the agents are uniformly distributed between 0 and 1 ($p_i$ = [0, 1]), this model reproduces a classical percolation model (Stauffer, 1994): when the diffusion ends the agents that have decided to see the movie are linked in a single cluster. If the cluster of agents that have seen the movie is large enough to touch the borders of the lattice, percolation has occurred and a hit is reported. Conversely, if percolation does not occur, a flop is reported. A full rational choice perspective would assume that all agents have perfect knowledge of the movie, and the proportion of visitors would equal the proportion of agents for whom the quality exceeds the individual preference. The classical percolation model demonstrates that when information is propagated through a social network, the success of the movie depends on whether or not its quality exceeds the percolation threshold. When the quality of the movie is below the percolation threshold, too few people visit it for the information to disperse through the whole population. Islands of uninformed agents remain and several agents, that would go to see the movie ($q > p_i$), do not go because they are not informed. As the information does not reach its potential public, the movie becomes a flop. When the movie quality is (sufficiently) above the percolation threshold, the information reaches most of the agents, and hence most of the potential adopters actually visit the movie. This kind of simulation models have the merit of describing innovation diffusion through percolation techniques, and in this way relate hits or flops to decision-making rules of the individual agents.

The assumptions of a regular network and fixed individual preferences are very strong and not supported empirically (De Bruyn and Lilien, 2004; Dodds et al. 2003).

During the last decade, more realistic social network models have been introduced and applied in the social sciences (Amaral et al. 2000; Barabasi and Albert, 1999; Delre et al. 2007b; Janssen and Jager, 2003; Watts and Strogatz, 1998). In the field of computational physics, several papers have studied how diffusions spread into different network structures simulating the diffusion of epidemics and viruses (Newmann and Watts, 1999; Newmann, 2002; Pastor-Satorras and Vespignani, 2002; Watts, 2002). Building on this stream of literature, we extend percolation models by formalizing more realistic decision-making for the agents, and by using more realistic social networks that also include constraints on the maximum number of contacts consumers can have (Amaral et al. 2000).

## 2.3 An Agent based Model for Innovation Diffusion

In the new agent based model for innovation diffusions as proposed in this chapter, agents decide according to a simple weighted utility of individual preference and social influence. In (2.1), $U_{ig}$ is the total utility of consuming the new product, which is composed of a social utility part $x_i$ and an individual utility part $y_{ig}$:

$$U_{ig} = \beta_i \cdot x_i + (1 - \beta_i) \cdot y_{ig} \tag{2.1}$$

The importance of the social versus individual utility is weighted by $\beta_i$, where $\beta_i$ can vary between 0 and 1. When $\beta_i$ is low, agent $i$ is very individualistic, and consequently it is hardly influenced by its neighbours. On the other hand, when $\beta_i$ is high, agent $i$ is very socially susceptible and a large part of its utility depends on what its neighbours do. Similarly, the average of $\beta_i$ ($\overline{\beta}$) determines which kind of market is simulated. When $\overline{\beta}$ is low the population of agents is more individualistic and it represents markets such as house furniture and durables; when $\overline{\beta}$ is high the population is more socially susceptible and it represents markets such as clothes. Social utility is formalized as:

$$x_i = \frac{\sum_j w_{ij}}{\sum_j a_{ij}} \tag{2.2}$$

Here, $x_i$ is the fraction of $i$'s neighbours that has already adopted ($A$ is the adjacent matrix indicating the contacts agents have with other agents and $W$ is a matrix indicating the contacts agents have with other agents that have already adopted). The formulation of the individual utility is captured in (2.3):

$$y_{ig} = \frac{q_g^{\gamma}}{q_g^{\gamma} + p_i^{\gamma}} \tag{2.3}$$

Here, $p_i$ is the individual preference of agent $i$, $q_g$ is the quality of product $g$. For large values of $\gamma$, if $q_g > p_i$ the individual utility is very close to 1 otherwise it is very close to 0. We choose a value for $\gamma$ large enough in order to obtain a bifurcation of the individual utility of the agent. In all simulation experiments we set $\gamma = 50$.

Agent $i$ buys product $g$ when it has been informed about the product, and the utility of the product is higher than its minimum utility requirement. This latter requirement is formalized in (2.4):

$$U_{ig} - U_{min,i} \geq 0 \tag{2.4}$$

The minimum utility requirement $U_{min,i}$ indicates the aspiration level of agent $i$. If $U_{min,i}$ is high, the agent is hard to satisfy and only adopts if the utility of the product is very high. If $U_{min,i}$ is low, the agent is very easy to satisfy and it adopts easily.

A market simulation starts by letting a small percentage of the population $\delta$ to adopt the product for free (for all simulation experiments we set $\delta = 0.5\%$). Once agent $i$ has adopted, it informs its neighbours about the quality of the product. Then, at the next time steps those informed neighbours compute their utility of consuming the product using (2.1), (2.2), and (2.3), and they decide whether to adopt or not according to (2.4). The simulation ends when no more agents adopt anymore. In this model, we assume the followings:

1. Agents are positioned in a social network. The social network is a connected graph where agents are nodes and links between agents are arcs. The graph is fully connected which means that a path between any couple of agents always exists (Wasserman and Faust, 1994).
2. Information can be passed from agent $i$ to agent $j$ if and only if there is a link between $i$ and $j$.
3. The percentage of initial adopters ($\delta$) is fixed and the selection of these adopters is exogenous and at random.
4. Choices are binary: there exists only one product and agents decide to buy or not to buy (Solomon et al. 2000; Weisbuch and Stauffer, 2000).
5. The population of agents is heterogeneous concerning social susceptibility and individual preference ($\beta_i$, $U_i$ and $p_i$ vary uniformly between 0 and 1).
6. Spread of information and social influence are separated phenomena. When an agent is informed about the existence of the product $g$ and its quality, it decides to buy or not to buy. If it buys the product, it informs its neighbours, otherwise it does not. In contrast to percolation models without social influence, in our model it is possible that an agent first does not adopt when being informed about the product, but later, when several neighbours have adopted, it may decide to adopt as well because of the increased social utility of the product. Hence, after being informed about product $g$, agent $i$ decides to buy or not at all successive time steps of the simulation.

### 2.3.1 Different Networks of Consumers

Traditional simulation models assume the agents to be positioned in a network with a rather restrictive structure, such as the regular lattice. We study the effects of different graph structures on the degree of the innovation diffusion. In particular, we focus our attention on a particular network structure: the scale-free network.

The shape of a scale-free network is such that many agents have a few neighbours whereas a few agents have a lot of neighbours. The scale-free network is a network where the probability for each node of having $n$ number of neighbours decays as a power law ($P(n) \sim n^{-\lambda}$, with $2 \geq \lambda \geq 3$) (Barabasi and Albert, 1999). This scale-free network is based on preferential attachment (Ijiri and Simon, 1974), i.e., when a new node *i* is added to the network, it is attached to node *j* with a probability that is proportional to the number of links that *j* already has. In large networks, there will be a few agents having a very large number of neighbours, and a large number of agents having just a few neighbours.

Although the scale-free network structure of Barabasi and Albert (1999) permits to have heterogeneous agents concerning the number of neighbours, this structure is often unrealistic from a social and an economic point of view because people often have constraints in building links with other people. This is why we adopt a more realistic version of the scale-free network (Amaral et al. 2000). Here, when a new node is attached to the network, the probability of all the other nodes of being selected for the attachment is still proportional to the number of nodes they already have but it decays exponentially due to a fixed probability *h* to become inactive at any moment of the process. Figure 2.2 shows the frequency of nodes having a given number of links for two different values of *h*. The scale-free network of Amaral et al. (2000) also yields a power law distribution of links for low connected links, but the number of links decays faster when the probability *h* increases. In networks with 100000 agents, when $h$=0.00001, the most connected agent (network hub or VIP) has about 60000 links and when $h = 0.01$, the most connected agent has about 250 links. We call the former a *central network* because most of the agents are connected with a few central agents and the latter a *disperse network* because the network is more stretched. In section 2.4.3.1 we study how these two structures affect the diffusion.

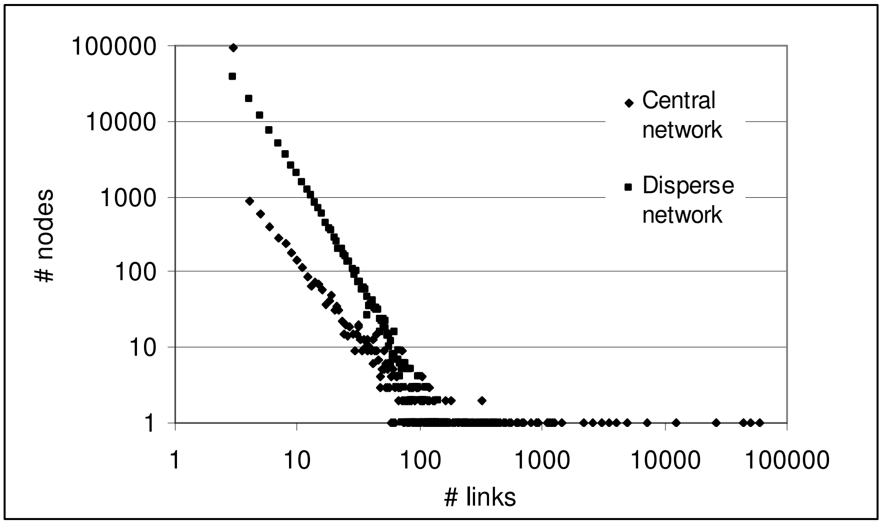



*Figure 2.2. Frequency of nodes for the number of links they have in two social networks where the probability of each node of becoming inactive is varied (h=0.01: disperse network and h=0.00001: central network)*

Our formalization of social network structures further considers weighted networks. In deciding whether to adopt or not, consumers may be differentially influenced by those they are connected with (Barrat et al. 2004; Leenders, 2002). In particular, we consider two cases: (a) the influence is equal for all the neighbours and (b) the influence of each neighbour is proportional to the number of links it has. The second case models the notion that more connected people exert higher social influence, not only because they have more chances to contact other people but also because they are considered more important. We changed $x_i$ in (2.2) such that the social influence an agent obtains from neighbours can vary between these two cases:

$$x_i = c \cdot \frac{\sum_j w_{ij}}{\sum_j a_{ij}} + (1-c) \cdot \left( \frac{\sum_j \left[ \left( \sum_k w_{ij} \cdot a_{jk} \right) - 1 \right]}{\sum_j \left[ \left( \sum_k a_{ij} \cdot a_{jk} \right) - 1 \right]} \right) \qquad (2.5)$$

Here, $\sum_j \left[ \left( \sum_k w_{ij} \cdot a_{jk} \right) - 1 \right]$ counts $i$'s neighbours of neighbours that have already adopted and $\sum_j \left[ \left( \sum_k a_{ij} \cdot a_{jk} \right) - 1 \right]$ counts the $i$'s neighbours of neighbours. The parameter $c$ weights the effect described above: when $c$=0, the effect of each neighbour is proportional to the number of other neighbours it has; when $c$=1, the effect of any neighbour is the same.

In the discussion so far, we assumed all network structures to have bi-directional links. Here, we also investigate diffusion patterns in directed networks, which make our network structures more realistic. It is very plausible that social influence among people is exerted only in one direction, especially in marketing contexts. For example, in the clothing market it is much more common that normal people observe what VIPs are wearing than the opposite way. Again, we consider two cases: (a) the probability of directing the link from $i$ to $j$ is simply 0.5 and (b) the probability of directing the link from $i$ to $j$ depends on the number of links that $i$ and $j$ have, i.e. the more (less) links $j$ has compared to $i$, the more (less) likely that $i$ is directed to $j$. For the latter specification, we assume that among two neighbours it is more likely that the more connected agent attracts the attention of the other. The re-linking process takes each link between node $i$ and $j$ and directs it with a probability $p$ as specified in (2.6). The parameter $d$ weights the two extreme cases. When $d$=1, we have case (a) and when $d$=0 we have case (b).

$$p(i \rightarrow j) = \frac{\sum_i a_{ji} - d \cdot \left[ \frac{1}{2} \cdot \left( \sum_i a_{ji} - \sum_j a_{ij} \right) \right]}{\sum_j a_{ij} + \sum_i a_{ji}} \qquad (2.6)$$

In section 2.4.3.2 and section 2.4.3.3 we study whether and how weighting and directing the links, as modelled through the parameters $c$ and $d$ respectively, affect the innovation diffusion.

## 2.4 Simulations: Experiments and Results

### 2.4.1 Effects of Social Network Structures

To replicate the percolation model of Solomon et al. (2000) with our innovation diffusion model and, to test different network structures, we let agents to have only individual preferences ($\beta_i$ = 0), we draw the minimum utility for adopting from a uniform distribution ranging from 0 to 1 ($U_{min,i}$ = [0, 1]), and we set the quality of the product at 0.5 ($q_g$ = 0.5). Finally, individual preferences vary from 0 to 1 on a uniform range of 0.5 (examples are $p_i$ = [0, 0.5], $p_i$ = [0.25, 0.75] and $p_i$ = [0.5, 1.0]). Moving the average of $p$ ($\overline{p}$) from 0.25 to 0.75, we simulate different populations having low and high individual preferences. The simulation is conducted with only 900 agents because these are already enough to replicate percolation models' results and to observe effects of different social network structures. Moreover, for each experimental setting we conducted at least 30 runs for each condition to guarantee that the mean and the standard deviation of each condition converged to stable values.

Whereas the percolation model is originally based on a regular lattice, empirical results indicate that people are connected not only locally, but they also use more remote links (Dodds et al. 2003; De Bruyn and Lilien, 2004). Moreover, some people use more links than others when deciding to adopt a new product. To study how such network assumptions affect the diffusion of innovations, we study the effect of different network structures, namely agents with complete information, agents in a regular lattice and agents in a scale-free network. Furthermore, we increase the average preference of the agents $\overline{p}$ from 0.25 to 0.75 in discrete steps of 0.025. We compute the average fraction of agents $f$ adopting the product at the end of the simulation run.

Simulation results demonstrate that the structure of the network has strong effects on the diffusion outcome (Figure 2.3). When agents have complete information, the simulation reproduces the line $f = \overline{U}$. However, for the other two structures the fraction of agents adopting the product approaches this upper curve only when agents' preferences are relatively low. In a regular lattice percolations always occur for conditions where the average preference of the population is less than the percolation threshold ( $\bar{p}$ < 0.455). In this condition information reaches almost all agents and those agents for whom $U_{ig} > U_{min,i}$ adopt the innovation. When $\bar{p} \geq 0.455$, after a certain short time the spreading of information stops and only a fraction of the agents for whom $U_{ig} > U_{min,i}$ adopts. Here, the non-adopting agents do not inform their neighbours and, as a consequence, information does not reach many agents in the network. Consequently a number of agents that potentially would adopt do not do it because they have not been informed about the innovation. These results replicate the results of the percolation model (Solomon et al. 2000) showing that a small change of average agents' preferences may cause the innovation to become either a hit or a flop. Furthermore, these results show that the percolation model differs from a hypothetical situation where agents have both complete information about the innovation and do not depend on their neighbours to obtain information on the quality of the new product. In the case of a scale free network, compared to a regular lattice, the information spreads easier through the population and hence more potential consumers are informed. The scale-free network performs close to the complete information case, thus indicating that it is very efficient in transmitting information. Only when the preferences of the agents are really much larger than the quality of the innovation, the fraction of adopters drops considerably compared to the complete information case. This is caused by the effect that the proportion of agents that do not adopt increases, and hence they do not inform other agents. Yet it can be seen that in a scale-free network a large proportion of the potentially interested agents is informed, as in the medium case ( $\bar{p}$ = 0.5) still about 80% of the potential adopters is informed and half of them adopts. Thus, the scale-free network is much more efficient in spreading information, it approaches the perfect knowledge curve and it smoothens the percolation effect.

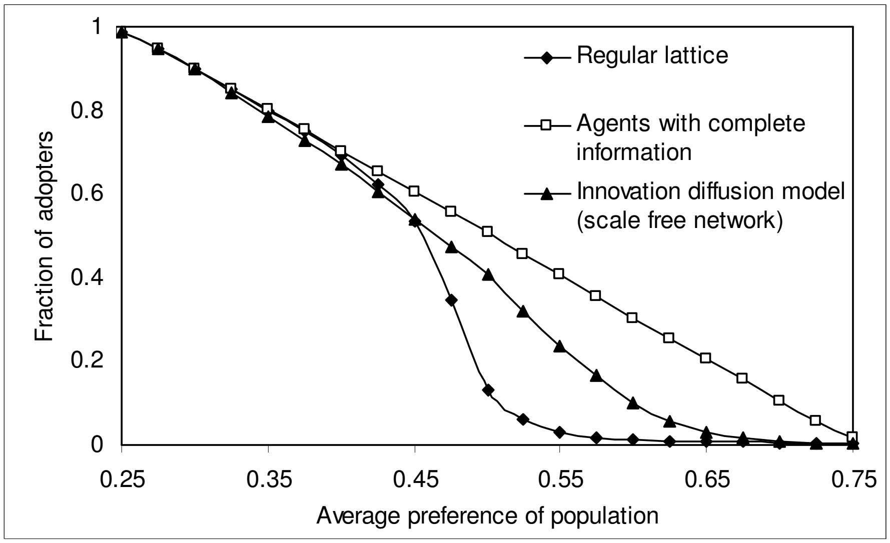



*Figure 2.3. Effects of network structures and average preference on final fraction of adopters.*

The shape of the network not only affects the degree to which a product diffuses, but also the speed of the diffusion process may differ considerably. In Figure 2.4 we present the average results of 20 runs for the condition where $p_i$ = [0, 0.5], thus involving agents with relative low preferences compared to the quality of the movie ($q_j$ = 0.5). In order to decelerate the speed of the diffusion in both networks, we updated agents with probability 0.3. For these parameters, and in all the 20 repetitions of the run, we observe an almost complete diffusion of the innovation (always $f >= 0.9$). The Figure 2.4 represents the fraction of adopters during the time of the diffusion.

We observe that in these favourable conditions for diffusion, the scale free network spreads the diffusion much more rapidly than the ring torus. On the one hand, in the scale free network, an almost complete diffusion is reached just in less than 40 steps. This is due to the fact that hubs are informed sooner by early adopters and if they adopt, they can inform easily the rest of the network. On the other hand, the diffusion in the ring torus spreads slowly. This indicates that also when the fraction of agents seeing the movie is similar for the scale free network condition and the ring torus condition, information and diffusion spread faster in the former than in the latter.

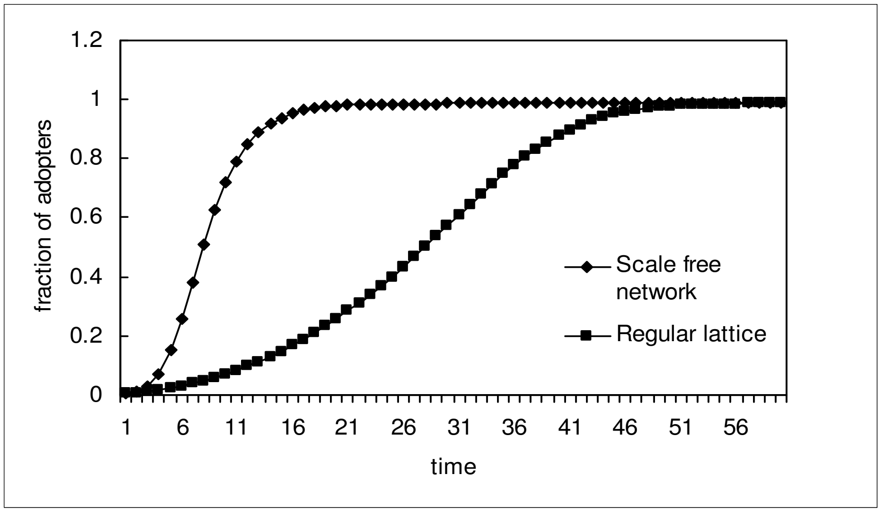



*Figure 2.4. Speed of the Diffusion in the Scale Free Network and in the Regular Lattice.*

### 2.4.2 Agents' Characteristics during the Innovation Diffusion

Who adopts first? And who adopts later? Which are the characteristics of the agents that adopt at the beginning, during and at the end of the diffusion? We studied the characteristics of adopters during the time of the simulations in the scale free network. We set the model with the following values: $p_i$ = [0, 0.5], $U_{min,i}$ = [0, 1] and $\beta_i$ = [0, 1] and we collected averaged values of 20 runs. For these conditions the innovation was completely diffused in 10 time steps ($f$ =0.848). In Figure 2.5 we show the characteristic S shaped penetration curve of the diffusion and in Figure 2.6 we show the average number of contacts adopters have during the time of the diffusion.

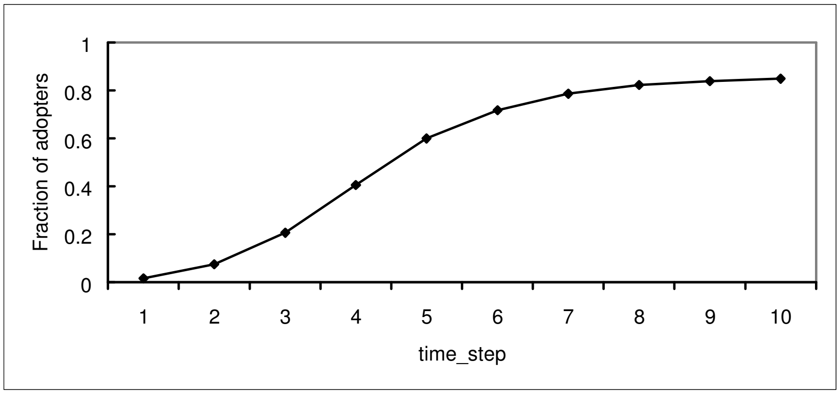



*Figure 2.5. Fraction of adopters during the time of the innovation diffusion in the scale free network.*

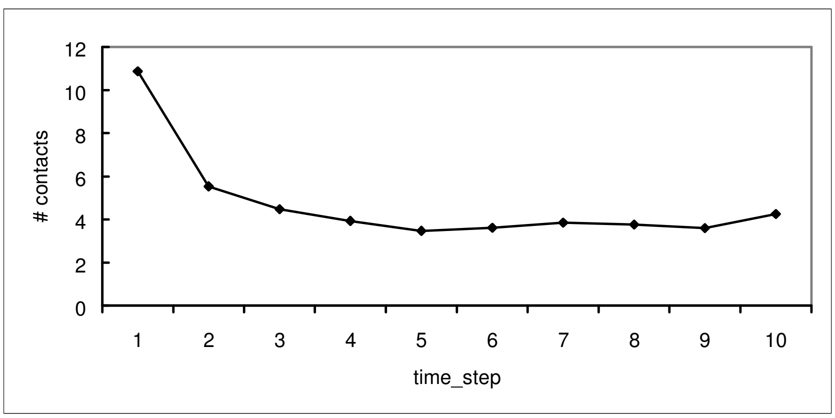



*Figure 2.6. Number of adopters' contacts during the time of the innovation diffusion in the scale free network.*

Results confirm that indeed agents that adopt at the beginning have many contacts with other agents and agents that adopt later have on average the same number of contacts (Coleman, 1966; Rogers and Shoemarker, 1971; Valente 1995). To have more contacts means to have more chances to get information about the innovation and more chances to adopt. In our innovation diffusion model, the number of contacts of the adopters seems to be inversely correlated with the time of the adoption. This indicates that the power of social networks resides in its capacity to spread information very quickly through the hubs. Finally, for the same values of the parameters, we also checked the averages of the $\beta_i$ values of the adopting agents during time (Figure 2.7).

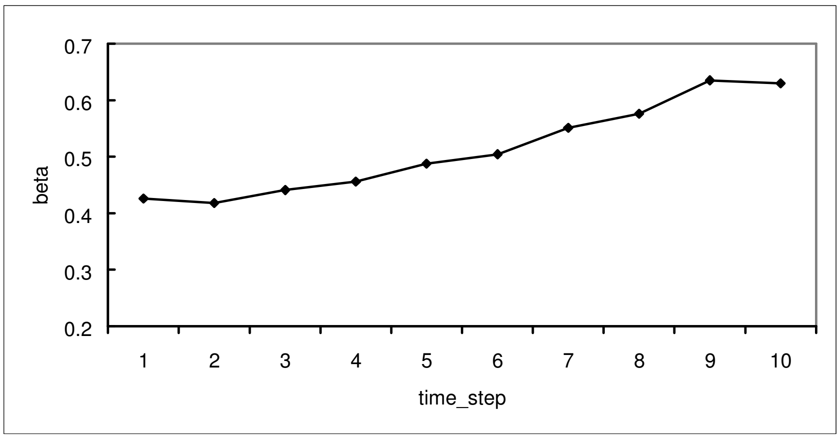
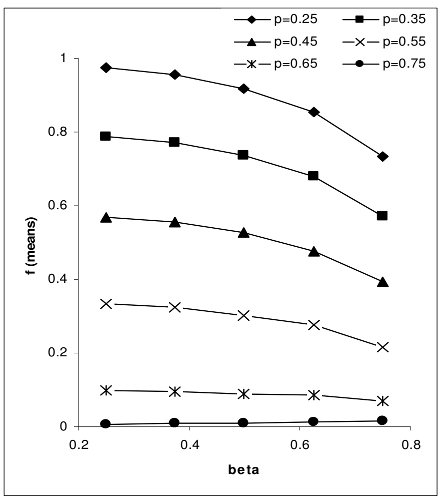



*Figure 2.7. Social susceptibility of adopters during the time of the innovation diffusion in the scale free network.*

Results show that the later agents adopt, the higher their values of $\beta_i$. Agents with high value of $\beta_i$, usually tend to wait and to follow what others do. At the beginning they do not adopt because not enough neighbours adopted but later, these agents are more likely to adopt if a sufficient number of other agents in their social network already adopted. On the contrary, agents adopting at the beginning have higher personal preference: at the early stages of the diffusion, early adopters and innovators adopt comparing the quality of the innovation and their personal preferences and they are only slightly influenced by neighbours that have not adopted yet.

### 2.4.3 High Social Influence versus Low Social Influence

Innovation diffusion theory indicates that consumers vary in the extent to which they experience social influence (Blackwell et al. 2001; Granovetter, 1983; Rogers, 1995). Therefore, we perform a series of experiments in which we vary the average $\beta$ of the agents ( $\overline{\beta}$ ). The higher $\overline{\beta}$ is, the more important the behaviour of neighbours becomes in the total utility of the innovation. Stated differently, the higher $\overline{\beta}$ gets, the more socially susceptible the simulated market becomes. We perform experiments for thirty conditions. We select 5 values for $\overline{\beta}$ ($\overline{\beta}$ = {0.25, 0.375, 0.5, 0.625, 0.75}) and 6 values for $\overline{p}$ ($\overline{p}$ = {0.25, 0.35, 0.45, 0.55, 0.65, 0.75}). We perform simulations with 100.000 agents connected in a scale-free network where agents have at least 3 links. Simulations run for 900 time steps and for all other decisions on the experiment, we adopted the design of the simulation described in section 2.4.1. Also in this case we run at least 30 runs for each condition making sure that means and standard deviations of the runs converge. Figure 2.8 shows the means and the standard deviations of the runs for the conditions specified above.



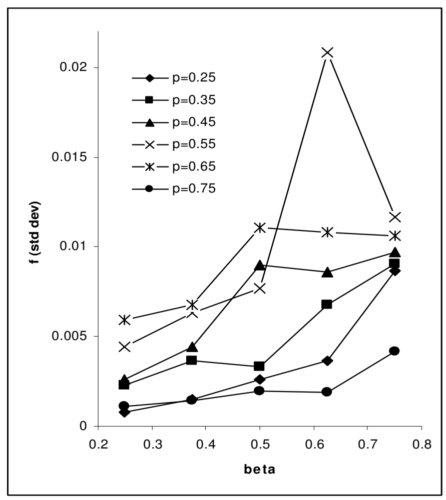




*Figure 2.8. Left graph: Averages of the diffusions at the end of the simulation runs for different levels of individual preferences and social influences; right graph: standard deviations of the diffusions for different levels of individual preferences and social influences.*

The graph on the left side of Figure 2.8 indicates that the diffusion of the innovation is hampered by high values of $\overline{\beta}$. A high value of $\overline{\beta}$ implies that social influence to adopt is high only if there are many neighbours that have already adopted. However, at the beginning of the diffusion only a limited number of consumers adopt.

Consequently, the exerted social influence to adopt remains low and the diffusion may not take off (see also Delre et al. 2007a). Hence, the final fraction of adopters is lower than when individual preferences mostly determine the decision of the agents. However, the decrease of final adopters is not proportional to the level of social influence. The decrease in the fraction of adopters is not very relevant when social influence drops from $\overline{\beta}$ = 0.25 to $\overline{\beta}$ = 0.375 if compared to the decrease of adopters that we observe when social influence drops from $\overline{\beta}$ = 0.675 to $\overline{\beta}$ = 0.75. Especially when $\overline{p}$ is lower than $q_g$, when social influence is low ($\overline{\beta}$ = 0.25 and $\overline{\beta}$ = 0.375), the critical mass is reached, social influence helps the spreading of information and innovation diffuses easily through the population. Agents that do not adopt are just those with very high $U_{min}$. On the contrary, when social influence is high ($\overline{\beta}$ = 0.625 and $\overline{\beta}$ = 0.75) the critical mass is not reached and social influence hampers the diffusion. The few agents that do adopt are not sufficient to ignite the diffusion and they remain exceptions in the population. Consequently, the fraction of adopters remains low.

The graph on the right side of Figure 2.8 reports the standard deviations of the 30 simulation runs for each condition. When different runs of similar simulations (with the same parameters' values) result in very different levels of market penetration, the standard deviation becomes high indicating that that particular market is uncertain and the success of the product is more difficult to predict. Figure 2.8 shows that uncertainty, as expressed in the standard deviation of market penetration, is high for intermediate levels of $\overline{p}$. When agents' preferences are much lower or much higher than the product quality, the uncertainty is low because the product always or never spreads. However, at intermediate levels of $\overline{p}$ uncertainty is high because sometimes the innovation spreads and sometimes it does not. Figure 2.8 shows also that the uncertainty of the innovation success increases with high values of $\overline{\beta}$. At the beginning of the diffusion process, highly socially susceptible agents do not consider the individual advantage of the innovation and they do not adopt because other agents have not adopted yet. This results in a freezing situation where nobody adopts because nobody else has already adopted. However, if the innovation succeeds to reach a sufficient number of adopters, then high socially susceptible agents are affected by the opposite effect joining those that have already adopted. Consequently in this case the simulation results depend more on the randomness of the model indicating more uncertainty and lower predictability of the innovation success.

### 2.4.4 Different Markets and Different Networks

As mentioned in section 2.3.1, the social utility $x_i$ can be changed to test different hypotheses of social influence. In section 2.4.1 we have shown how different social structures cause different diffusion patterns and that the scale-free network is very efficient in spreading the innovation. However, for social sciences in general and marketing field in particular, traditional scale-free networks may be unrealistic for several reasons. First, VIPs (or network hubs) cannot always have an infinite number of neighbours. Therefore, we attach a cost constraint to each contact an agent has, as described in section 2.3.1 (Amaral et al. 2000). In this way, using two values of the parameter $h$, we obtain two kinds of networks, central network and disperse network, and in section 2.4.4.1 we study how the innovation diffusion process is affected by these different network formalizations. Second, while we have assumed so far that each neighbour exerts equal influence on the agent's decision-making, it is plausible that people assign different importance to their peers and friends and that the social influence exerted to them may vary (Barrat et al. 2004; Granovetter, 1978). In section 2.4.4.2, we relax this assumption and we investigate how diffusion patterns change when the social influence consumers receive from neighbours is weighted according to the number of other neighbours they have. Finally, in section 2.4.4.3, we study the effects of directed networks. We let the direction process of the scale-free network being governed by the parameter $d$ as specified in (2.6) and we observe changes in the final market penetration of the innovation.

#### 2.4.4.1 Centralized Networks versus Disperse Networks

For both central networks and disperse networks, with strong and weak network hubs respectively, we perform the same experimental design as in section 2.4.3. To assess the effects of individual preference and social influence, we perform an analysis of variance (ANOVA) testing and estimating the effects of $\overline{\beta}$, $\overline{p}$, and $h$ on the average degree of the diffusion (Table 2.1 and Figure 2.9). Here it is important to notice that, given the high number of agents and simulation runs, it is very likely that these analysis yields significant effects. Thus, the results have to be interpreted more in a relative sense by comparing the signs and the sizes of different effects than in an absolute sense focusing on the significance (see also Goldenberg et al. 2001). As expected from the results presented in sections 2.4.1 and 2.4.3, $\overline{p}$ and $\overline{\beta}$ have negative effects on the penetration of the innovation. Figure 2.9 shows that also $h$ has a negative effect on the market penetration. The effect of $h$ indicates that central networks are much more efficient in spreading the innovation, compared to disperse networks. In disperse networks ($h$ = 0.01) agents have a strong limit to the number of neighbours and hubs are connected only to a small proportion of the complete population. Then, in the disperse network different areas of the network are less closely connected than in the central scale-free networks. Thus, information about the product needs to travel via more agents to reach another area of the network of consumers and, consequently, the information about the new product can get trapped easier.

The parameter $h$ has relevant interaction effects both with $\overline{p}$ and with $\overline{\beta}$. The interaction between $\overline{p}$ and $h$ is straightforward: when the preferences of the agents are too high, the diffusion will hardly spread neither in the centralized nor in the disperse network. More interesting is the interaction between $\overline{\beta}$ and $h$. Figure 2.9 (left graph) shows that the negative effect of social influence is much more crucial in the disperse networks than in the central network. When the new product is adopted by the first agents, they communicate it to their neighbours, often the hubs of the network. At this point, the social influence a single adopter exerts on a hub is very low, because this influence is averaged over the influences of all neighbours, including the non-adopters. This non-adoption effect on hubs becomes stronger when agents are more social susceptible (higher values of $\overline{\beta}$). However, if a hub does happen to adopt, it informs many connected agents, thus contributing to the success of the diffusion. In centralised networks, even a single adopting hub can spread the information to almost all agents. In disperse network, however, adopting hubs can spread the information only to a small proportion of the entire population. An increase in social influence has a negative impact on the diffusion, but, especially in centralised networks, hubs can contrast this effect due to the large number of links they have, which allows them to spread the information about the new product to the rest of the agents.

The strong information spreading power of hubs also has a strong effect on the uncertainty of the market. The uncertainty regarding the take off and the final success of a diffusion is much higher in disperse networks than in centralized networks (Figure 2.10). In centralized networks, the high visibility of hubs makes almost the entire market aware of the new product and agents can decide according to their personal preferences and the quality of the new product. In disperse networks this does not happen that often, because the information cannot spread that easily. Sometimes the information stops spreading at the early stages of the diffusion, and many agents are not aware of the innovation's existence, causing the new product to fail. Some other times information does spread, for instance because initial adopters have many links or because they are in different strategic areas of the network. This causes that many agents are being informed about the new product, and a successful diffusion is mainly determined by agents' preferences and product quality.

Table 2.1

ANOVA model for the effects $\overline{\beta}$, $\overline{p}$, and $h$ on the average degree of the diffusion

| | df | Sum of squares | F | Sig. | Partial Eta Squares |
|---|---|---|---|---|---|
| intercept | 1 | 161.38 | 26837.35 | < 0.01 | 0.94 |
| h | 1 | 23.83 | 3962.31 | < 0.01 | 0.69 |
| beta | 4 | 11.79 | 490.26 | < 0.01 | 0.53 |
| p | 5 | 132.45 | 4405.11 | < 0.01 | 0.93 |
| h*beta | 4 | 2.40 | 99.86 | < 0.01 | 0.18 |
| h*p | 5 | 9.33 | 310.18 | < 0.01 | 0.47 |
| beta*p | 20 | 14.08 | 117.11 | < 0.01 | 0.57 |

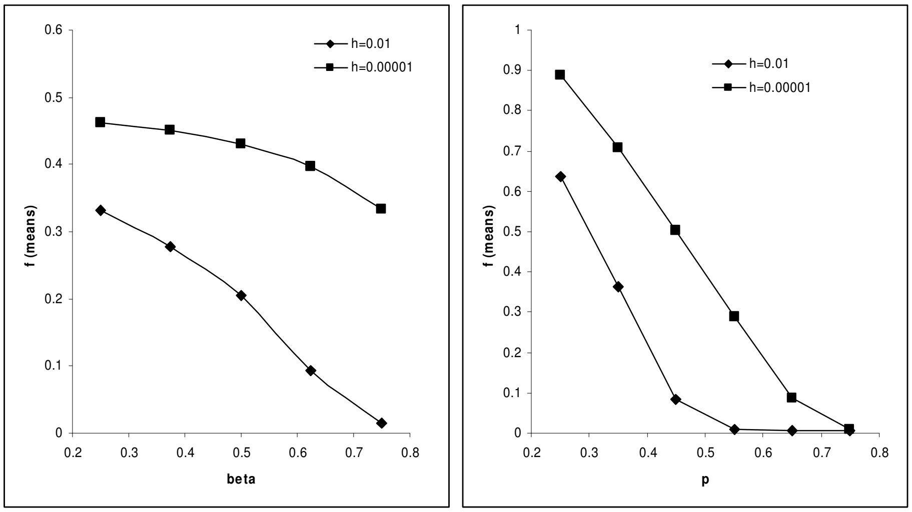



*Figure 2.9. Left graph: social influence effects on the average degree of the diffusion; right graph: the effects of individual preferences on the average degree of the diffusion.*

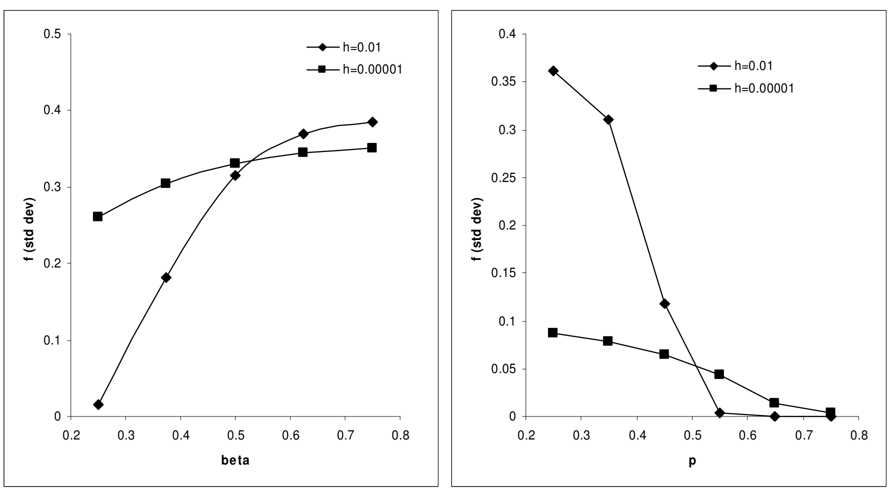



*Figure 2.10. Left graph: social influence effects on the standard deviations of the diffusions; right graph: the effects of individual preferences on the standard deviations of the diffusions.*

2.4.4.2 Weighting the Social Influence of Neighbours

Social influence that consumers exert on each other varies according to the status, the leadership and the power they have (Blackwell et al. 2001; Flynn et al. 1996; Rogers, 1995). Here we investigate how a different specification of the social utility affects the diffusion process. In particular, we weight each contact an agent has proportionally to the number of other contacts that its neighbours have. The parameter *c* in (2.5) varies from 0 to 1. We perform simulations for 3 values of *c* ($c = \{0.0, 0.5, 1.0\}$), where $c$=1 corresponds to equal weighting of connections as used in the previous simulation runs. The results are presented in Table 2.2 and the interaction effects between *c* and the other parameters are shown in Figure 2.11.

Table 2.2

ANOVA model for the effects of $\overline{\beta}$, $\overline{p}$, *h* and *c* on the average degree of the diffusion

| | df | Sum of squares | F | Sig. | Partial Eta Squares |
|---|---|---|---|---|---|
| intercept | 1 | 548.09 | 77734.09 | < 0.01 | 0.94 |
| h | 1 | 84.89 | 12039.20 | < 0.01 | 0.69 |
| c | 2 | 1.08 | 76.57 | < 0.01 | 0.03 |
| beta | 4 | 30.42 | 1078.67 | < 0.01 | 0.45 |
| p | 5 | 424.94 | 12053.53 | < 0.01 | 0.92 |
| h * c | 2 | 0.43 | 30.84 | < 0.01 | 0.01 |
| h * beta | 4 | 10.53 | 373.26 | < 0.01 | 0.22 |
| h * p | 5 | 31.29 | 887.69 | < 0.01 | 0.45 |
| c * beta | 8 | 0.13 | 2.35 | 0.02 | 0.00 |
| c * p | 10 | 0.32 | 4.59 | < 0.01 | 0.01 |

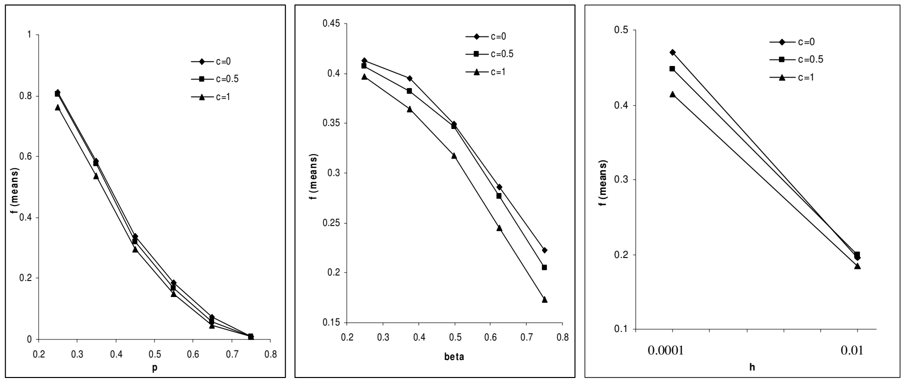



*Figure 2.11. Left graph: the interaction effect of weighted networks and individual preferences on the degree of diffusion of the innovation; central graph: the interaction effect of weighted networks and social influence; right graph: the interaction effect of weighted networks and network structures.*

Table 2.2 and Figure 2.11 indicate that *c* has a negative effect on the degree of the diffusion meaning that when agents receive more social influence from the more connected agents, then the innovation tends to be adopted more easily. However, this effect is very small (partial eta squared is 0.028) when compared to other effects (individual preference, social influence and network structure). Furthermore, the interaction effects of *c* with the other effects are negligible in size. Hence, although the effect exists, the degree of weighting connections by the number of connections these neighbours have, has limited consequences on the final adoption of the product.

#### 2.4.4.3 Directed Networks of Consumers

For the simulation experiments presented in this section, we use the same conditions as in section 2.4.4.1, but the simulation experiments are performed on directed networks. We assess the effect of changing the parameter *d* which governs the direction process, as described in section 2.3.1. Setting *d*=0 means that the chances of directing the link from *i* to *j* are proportional to the relative number of neighbours *i* and *j* have. On the other extreme, when *d*=1, the chances are purely random. We investigate three values of *d* (*d* = {0.0, 0.5 and 1.0}). Table 2.3 and Figure 2.12 presents the ANOVA model results for the effects of *d* and the other simulation parameters.

The effects of $\overline{\beta}$, $\overline{p}$, and $h$ remain negative and significant. Also $d$ has a negative and significant effect on the degree of the diffusion. This means that directing the links to the more connecting agents creates a stronger social influence to adopt. However, this effect is again very small (partial eta squared is 0.01) compared to the effects of other parameters. The more the network is directed to the more connected agents, the higher the penetration of the innovation. We can explain this effect considering the strength of the social influence. Suppose that $i$ and $j$ are connected and that $i$ has 8 neighbours and that $j$ has 4. If $j$ is directed to $i$, $i$ has already adopted and $j$ has not, then the social influence $i$ has on $j$ is one forth. On the other hand, if $i$ is directed to $j$, $j$ has already adopted and $i$ has not, then the social influence $j$ has on $i$ is one eighth. This means that, given all the other effects equal, directing the links to the more connecting agents creates a stronger social influence to adopt. However, the effect of the direction parameter and the interaction effects of $d$ with the other factors are also relatively small. The largest of these effects is the interaction with the distinction between central networks ($h$ = 0.00001) and disperse networks ($h$ = 0.01) (see the right graph of Figure 2.12). In central networks the directional effect is virtually zero, whereas in the disperse network the effect is somewhat larger. As already mentioned, the direction process affects the decision of the agents (whether to adopt or not), but it does not affect the exchange of information among agents. Overall the diffusion of the innovation depends much more on the flow of the information inside the network structure than on the directions of the social utility impact between agents.

Table 2.3

ANOVA model for the effects $\overline{\beta}$, $\overline{p}$, $h$ and $d$ on the average degree of the diffusion

| | df | Sum of squares | F | Sig. | Partial Eta Squares |
|---|---|---|---|---|---|
| intercept | 1 | 476.57 | 78486.05 | < 0.01 | 0.94 |
| h | 1 | 71.05 | 11701.54 | < 0.01 | 0.69 |
| d | 2 | 0.34 | 27.62 | < 0.01 | 0.01 |
| beta | 4 | 34.85 | 1435.07 | < 0.01 | 0.52 |
| p | 5 | 387.63 | 12767.72 | < 0.01 | 0.92 |

| | | | | | |
|---|---|---|---|---|---|
| h*d | 2 | 0.17 | 13.80 | < 0.01 | 0.01 |
| h*beta | 4 | 6.89 | 283.71 | < 0.01 | 0.18 |
| h*p | 5 | 27.71 | 912.69 | < 0.01 | 0.46 |
| d*beta | 8 | 0.08 | 1.76 | 0.08 | 0.00 |
| d*p | 10 | 0.17 | 2.72 | < 0.01 | 0.01 |
| beta*p | 20 | 42.409 | 349.21 | < 0.01 | 0.57 |

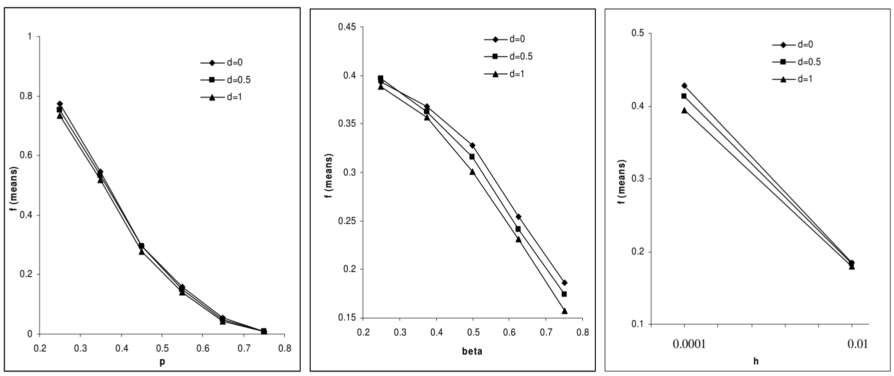



*Figure 2.12. Left graph: interaction effect of directed networks and individual preferences on the degree of diffusion of the innovation; central graph: interaction effect of directed networks and social influence; right graph: interaction effect of directed networks and network structure.*

## 2.5 Conclusions

In this chapter, we proposed a new agent based model for innovation diffusion. To enhance usefulness to social scientists and marketers for modelling innovation diffusion in a network of consumers, we modified and extended existing agent based models in several ways. First, we adopted the scale-free network structure, which is less restrictive than traditional structures and has been shown to be efficient in modelling the spreading of viruses and epidemics (Barthélemy et al. 2004; Barthélemy et al. 2005; Newman, 2002; Pastor-Satorras and Vespignani, 2002). Second, we altered the agent decision rules to account for the fact that consumers decide more deliberatively according to their individual preferences and that social influences play a determinant role (Buskens and Yamaguchi, 1999). Third, we modified the network structure by a) constraining the number of connections an agent may have, b) differential weighting of the connections, c) allowing for directed connections. In several simulation experiments, we tested our model and demonstrated the effects of these network features.

The utility a consumer derives from a product is partly a function of the adoption by other consumers in the neighbourhood of that consumer (Granovetter, 1983). We found that such social influences may decrease the chances for the diffusion to spread significantly. If the quality of the innovation is high enough and the diffusion easily reaches the critical mass, the decrease of the number of final adopters is very small. On the contrary, if the innovation is of lower quality and it hardly reaches the critical mass, social influence becomes considerable and consumers do not adopt because their neighbours did not adopt. As a result, the final penetration of the innovation is substantially lower compared to the situation without social influence. Moreover, we found that the uncertainty about the innovation success also increases in more social susceptible markets. These results dissent with the common intuition that fashionable markets are easy to penetrate because consumers tend to copy each other (Gladwell, 2000; Rosen, 2000). Perhaps in real life it is much easier to notice the social influence exerted by adopters than the social influence exerted by non-adopters. We observe positive social influences only when new products do succeed to diffuse but we usually forget negative social influence playing the opposite effect. We showed that social influences can either have a positive effect on the diffusion of the innovation when a given critical mass is reached or a negative effect when the critical mass is not reached. Consequently innovation diffusion in such a market can be very uncertain.

We also investigated the effects of VIPS (or network hubs) on the individual decision-making of the consumers and on the final market penetration of innovations. If the VIPs have many connections with consumers, they have a large positive effect on market penetration of the innovation. The most important function of VIPs is to inform consumers about the new product. Hence, advertising the innovation through VIPs is strongly suggested for this type of markets. However, there are many markets where strong network hubs or VIPs do not exist. We showed that for such markets successful diffusions are less likely to happen. An example is the pharmaceutical market. The hubs of this market are the physicians that prescribe the medicine to their patients, but physicians have only a limited number of patients. Here, physicians are more numerous than VIPs and they do not have the information power VIPs have. Directing the advertisement to physicians permits to inform only a relatively small part of consumers. This is why, for this kind of markets, direct-to-consumer advertising could be an alternative strategy to stimulate the spreading of the new product in different areas of the network (Narayanan et al. 2004).

Finally, we investigated whether and how the weight of the social influence and the direction of this social influence affect the degree of the innovation diffusion. It is plausible that consumers with many relationships have a strong influence on the decision-making of other consumers. Indeed we found that when the weights are stronger for those neighbours that have more relationships, the innovation reaches higher degrees of penetration. However, this effect is relatively small compared to other network factors. A similar result was obtained when we considered the directions of the relationships. We found that the direction of the relationships among consumers does not substantially affect the final market penetration. VIPs do help the diffusion to spread into the network because they immediately spread information about a new product but VIPs do not have a particularly strong power of convincing consumers to adopt a new product, at least they do not have more social influence than other neighbours. Their strategic positions into the network of consumers help the penetration of the innovation because they make consumers aware but they are not able to influence consumers to adopt much more than what other consumers do. Because almost all consumers look at them, then the information spreads easily into the market. But this is not sufficient to guarantee a final success of the innovation with a high penetration of the diffusion. In this sense the effect of VIPs, such as the Oprah's effect, can be often overestimated. Their relation with other consumers is almost always unidirectional and the social influence they convey to normal consumers is not particularly stronger than the social influence conveyed by normal friends.

In this chapter, we demonstrated how agent based models can be used to study innovations both at the individual-level and at the market-level. We showed whether and how final market penetration depends on the network features of the market. In line with this project, other questions could be addressed providing little variations to this agent based model. They mainly relate to how to stimulate diffusion. For example in the context of viral marketing, how many and which type of consumers to use as seeds in the process? Is it more effective to address seeds that are mutually connected, or seeds that are dispersed in the population? What does happen when consumers preferences are not equally distributed all over the population but they cluster in different groups? Moreover there are also many other general questions that remain to be answered and that may encounter interesting insights using another model but a similar methodology (Garcia, 2005; Goldenberg et al. 2004; Lusch and Tay, 2004). Critical relevant questions are: what does happen in case of repeated purchases? What is the effect of mass-media strategies in supporting these diffusion processes? Answering these questions will further contribute to our understanding of the effectiveness of marketing strategies in relation to network topology and social influences.

# 3 Diffusion dynamics in small-world networks with heterogeneous consumers[2]

Diffusions of new products and technologies through social networks can be formalized as spreading of infectious diseases. However, while epidemiological models describe infection in terms of transmissibility, we propose a diffusion model that explicitly includes consumer decision-making affected by social influences and word-of-mouth (WOM) processes. In our agent based model consumers' probability of adoption depends on the external marketing effort and on the internal influence that each consumer perceives in his/her personal networks. Maintaining a given marketing effort and assuming its effect on the probability of adoption as linear, we can study how social processes affect diffusion dynamics and how the speed of the diffusion depends on the network structure and on consumer heterogeneity. First, we show that the speed of diffusion changes with the degree of randomness in the network. In markets with high social influence and in which consumers have a sufficiently large local network, the speed is low in regular networks, it increases in small-world networks and, contrarily to what epidemic models suggest, it becomes very low again in random networks. Second, we show that heterogeneity helps the diffusion. Ceteris paribus and varying the degree of heterogeneity in the population of agents simulation results show that the more heterogeneous the population, the faster the speed of the diffusion. These results can contribute to marketing strategies for the launch and the dissemination of new products and technologies, especially in turbulent and fashionable markets.

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[2] The work of this chapter is based on Delre et al. (2007b).

## 3.1 Introduction

Technological innovation drives the progress of societies. Any time a new technology, a new device, a new product appears into a society, its members have the chance to become aware of the innovation and to use it. In western societies people encounter new inventions and technologies on an almost daily basis. When these are consumed on an individual (or household) basis, single consumers (or households) can decide whether to adopt or not. The study of diffusion patterns of new products into society, from their launch to their successful adoption or failure to spread, closely involves managers and marketers whose interests are in disseminating new products into the society.

Recently marketers' attention has focused on the explosion of new fashions (Gladwell, 2000) and on the buzz that accompanies these explosions (Rosen, 2000). Especially in highly social susceptible contexts like clothes markets, many innovations emerge from minor events that are strongly related with the dynamics of local networks of friends. Then the new innovative fashion trend is adopted by some early adopters which are easily influenced by new trends and once the *critical mass* is reached, the diffusion and the number of adoptions get at their peaks. Almost all potential consumers decide to adopt and also laggards and sceptical consumers may decide to conform adopting the new product (Rogers, 1995). Throughout all this process, the social influence of other consumers' behaviours constantly affects the individual adoption. For example, somebody's decision of buying a cell phone partly depends on the number of friends and acquaintances already having one. If just a few of them have a cell phone, and she has no strong preference for using a cell phone, she would probably not feel an urgent need to buy one as well. However, if most of them use a cell phone, the social influence they have on her would become strong, and she may decide to buy one, despite her preference is not strong. Here we present an agent based model that formalizes the consumer decision-making including the social influence as part of her utility. This agent based model allows us to analyze how social influence is exerted into personal networks and how it shapes the macro diffusion of the innovation.

Most studies on innovation diffusion modelling are rooted in the work of Bass (1969). The Bass model formalizes the aggregate level of penetration of a new product emphasizing two processes of communication: (1) external influence via advertising and mass media, and (2) internal influence via WOM. The decision of a consumer is described as the probability to adopt the new product during time and it is assumed to depend linearly on these two forces. The first force is not related to previous adopters and it represents the external influence of mass media; the other force is related to the number of previous adopters and it represents the internal influence of WOM:

$$\frac{f(T)}{1-F(T)} = p + qF(T) \tag{3.1}$$

*f(T)/(1-F(T))* is the hazard function defining the probability of a consumer to adopt at time $t$, $p$ reflects the mass media influence and $q$ reflects the influence due to WOM. This basic Bass model fits very well to real data of durable goods, and many other variations of the model have appeared in order to explain different aspects of the diffusion at the aggregate level (for overviews see Mahajan and Muller, 1979 and Mahajan et al. 2000). The model is able to represent a cumulative S curve of adopters and the fast growth is generated by the social interaction between early and late adopters (Rogers, 1995). However, the Bass model assumes all consumers to be homogeneous. It does not specify at the micro level how the consumer decision-making changes during time and how consumers communicate and influence each other. One of the rare examples of micro-level models of diffusion process in a traditional economic framework is the work of Chatterjee and Eliashberg (1990). This study presents an analytical model of innovation diffusion based on an individual decision-making that determines the adoption of agents one by one. The decision of adopting depends on the characteristics of the consumers, namely the perception of the innovation, the personal preference and the perceived reliability of information. The model introduces heterogeneity in the individual parameters of the population of potential consumers and these specific parameters are tested by a pilot study conducted in an experimental laboratory setting. Chatterjee and Eliashberg's model generated much interest on the impact of heterogeneity on diffusion models (Bemmaor and Lee, 2002) and it represents a complete framework that links individual decision-making and aggregate dynamics of innovation diffusion processes. However, the analytical tractability of the model obliges to limited analysis of aggregated variables and of consumers characteristics. This holds both for the estimation of the parameters at the aggregate level and for the estimation of individual parameters in the laboratory experiments. Our agent based model can easily include heterogeneity in the population of consumers and it allows us to study how it affects the shapes of the diffusion curves.

Besides the work in line with the Bass model, much research on innovation diffusion has focused on computational models that investigate the patterns of innovation diffusion through social networks (Abrahamson and Rosenkopf, 1997; Goldenberg et al. 2000; Weisbuch and Stauffer, 2000). These models are based on the similarities between viral marketing dynamics and the diffusion of diseases (Moore and Newman, 2000; Newman, 2002; Dodds and Watts, 2005). They include a network with nodes and links, and a virus infecting the nodes travelling through the links. The nodes are consumers, links are the relations that consumers have among themselves and consumers are infected when they decide to adopt the innovation. Epidemic models explicitly define adoption rules and they are able to explain aggregate dynamics in terms of individual transmissibility. From a behavioural point of view, these models are extremely interesting because they permit to derive macro dynamics from micro hypothesis on individual decision making. However, in order to accept these models in social contexts, they need to be integrated with more realistic social processes like, as mentioned above, social influence and imitation. We propose a diffusion model that explicitly includes consumer decision-making affected by social influences and WOM processes. In fact the agents of our simulation model decide according to both their individual preference and the experienced social influence from other agents' behaviour. This model allows us to study diffusion patterns in time for different markets. In particular, we focus our analysis on very turbulent and fashionable markets where consumers highly affect each others' behaviours. Examples are clothes markets, electronic devices and music. Our model shows how in these kinds of markets the social structures connecting the consumers and the heterogeneity of the consumers significantly determine the shape and speed of the diffusion.

The chapter is structured as follows: in section 3.2 we review epidemic models; in section 3.3 we comment on threshold models in social science and how they are used in modelling herding behaviours; in section 3.4 we present our agent based model; section 3.5 reports results of simulations and finally in section 3.6 we report comments and conclusions.

## 3.2 Epidemics in Social Networks

A new product that invades a society is like a contagious epidemic that spreads in a population of humans or like a virus that is transmitted in a computers' network (Dodds and Watts, 2005). Thus, epidemic models can be very useful also in social and marketing contexts because they propose models that explain aggregate diffusion dynamics in terms of individual characteristics.

Most of the epidemic models are divided into two families: SIS (Susceptible, Infected, Susceptible) and SIR (Susceptible, Infected, Removed). The former assumes that nodes are initially susceptible and they become infected with probability $v$ if they are directly linked with one or more infected nodes. Then the infected node recovers and becomes susceptible again with probability $\delta$. When $\delta$=0, infected nodes cannot recover and the SIS model is converted into a SI (Susceptible, Infected) model. In the latter the same dynamics are assumed but once the node is infected, it never recovers, it just dies with probability $\gamma$ and it is removed from the network. For social and marketing purposes, we focus mostly on SIS and SI models because these are more relevant in social and marketing contexts: once somebody adopts a product she is not removed from the market; on the contrary, her decision of adopting affects other consumers.

In a SIS model, at the beginning of the spreading process, the diffusion of the disease involves only a few nodes of the network. These nodes infect each one of their direct neighbours with probability $v$. It has been found in random graphs that if $\lambda=v/\delta$ overcomes a given threshold $\lambda_C$, then the diffusion speeds up, the rate of diffusion increases in time infecting the majority of the network. Finally the rate of diffusion decreases only when almost all the population has been infected. If the rate of infection $\lambda$ cannot overcome $\lambda_C$, then the diffusion dies out and the majority of the network is not involved in the process of diffusion (Anderson and May, 1992). The structure of the network (number of nodes, distribution of the links, clustering coefficients) determines the speed and the degree of diffusion. Watts (2002) showed that diffusion in random graphs does not depend on the amount of initially infected nodes but on the connectivity of the network. In highly connected random graphs, the disease spreads easily because when a node is infected, it is likely that among its neighbours, there is someone that decides to adopt as well and the diffusion continues spreading. At each time step there is always some new node that is infected. Then, the diffusion process depends on the critical mass as described in classical innovation diffusion marketing models (Rogers, 1995; Mahajan and Muller, 1979): if the early adopters (the nodes that are infected at the beginning of the diffusion) reach the critical mass, the diffusion will finally succeed in reaching the whole potential population.

However, social and artificial networks often have global structures that are not random, but display stylized characteristics like power law distribution of the links, high clustering coefficients and short paths between any couple of nodes (Barabasi and Albert, 1999; Watts and Strogatz, 1998). Both analytically and with computer simulations, Pastor-Sartorras and Vespignani (2002) showed that in scale-free networks $\lambda$ approaches 0. With a multi-agent based model, Delre et al. (2004) and Delre et al. (2007c) found a similar result for diffusion of innovations in a population of social susceptible consumers: innovations are more likely to spread and be adopted by more consumers when consumers are linked in a scale-free network than in a regular lattice.

Also the small-world network structure has been extensively investigated. Newman and Watts (1999) and Moore and Newman (2000) investigated epidemic dynamics in the small-world area and they describe how the percolation threshold depends on the number of shortcuts[3]. They found similar results when they vary the *transmissibility* of the disease (the probability that a disease is passed from an infected to a healthy and susceptible node). These studies show that diffusion dynamics in the small-world networks are the same of those in the random networks if the degree of randomness is big enough and the percolation threshold is reached. This result is relevant especially for diffusion of infectious diseases because it focuses on the transmissibility of diseases.

However, from an economic and consumer behaviour point of view, there are two issues that appear to be problematic. The first is about the assumption of infectious

[3] A percolation threshold is the minimum probability for which an infinite regular lattice percolates (i.e. in a bi-dimensional regular lattice, cells are activated in such a way that a cluster reaches the borders of the lattice) (Stauffer, 1994). For this probability, the cluster scales extensively with the total number of the cells. Newman and Watts (1999) and Moore and Newman (2000) adopt the concept of percolation threshold to the small-world network graph. Here the percolation threshold is the minimum probability for which a giant component first form.

contacts. It is not always convenient to assume that all nodes are equally susceptible during the time of the diffusion. People, in particular consumers, decide to adopt a new product partly according to how much they are exposed to the product. Consumer adoption partly depends on what other consumers do (Granovetter and Soong, 1986). When an innovation has vastly spread into a market, also those that were initially sceptical about the innovation may decide to adopt. Nowadays there is a strong social pressure to adopt a cell phone because almost all the people have one. The second problem concerns the results of random networks: for social scientists it is difficult to accept the idea that random networks are as efficient as small-world network in spreading fads and fashions. Having a high clustered group of friends is a crucial factor in determining the adoption of the group. Usually, if the network is highly clustered and a fashion emerges in a cluster, the social influence towards the non-adopters is very strong and it is very likely that the fashion involves the entire cluster. Contrarily, if all friends of a consumer belong to completely different groups (like relationships in a random graph), the consumer would not fell a strong social pressure to adopt. Moreover, because in the small-world networks clusters are connected through shortcuts, it can be hypothesised that a cluster that has already adopted affects connected clusters that have not adopted yet. Both problems derive from an oversimplification of the metaphor between disease spreading and innovation diffusion. While epidemic models can assume a unique virus to spread into the network, social scientists have to distinguish at least between two different processes: diffusion of the information about the product through friends' connections and social influence that takes place in local groups and in personal networks.

Although some studies have reported the high performances of small-world networks in diffusion of knowledge (Cowan and Jonard, 2004) and consumption (Janssen and Jager, 2003), to our knowledge there is not an economic model that formalizes the emergence and the diffusion of innovations in the small-world networks in terms of local interactions. Here we present an agent based model that simulates the emergence of innovations in social networks. We conduct an extensive sensitive analysis of the model parameters and we draw the area of parameter space for which small-world network are more efficient in spreading the diffusion into the population of consumers.

## 3.3 Threshold Models in Social Networks

Threshold models have a relevant tradition in social science, especially in modelling collective behaviours (Granovetter, 1978; Macy, 1991). They formalize situations in which there is a population of individuals that decide either to be involved or not in a group behaviour. The focus of these models is on the social influence that adopters exert on those that have not adopted yet. Each individual has a *personal threshold* and if the size of the group is bigger than her personal threshold, then she decides to adopt the behaviour of the group. Threshold models formalize a positive feedback into the dynamics of the population: the more individuals are involved into the group behaviour, the more others will feel the social pressure to adhere to the group behaviour. If the group behaviour is able to involve enough individuals, its diffusion will easily take off because of this positive feedback. Otherwise it likely dies out. Similar distributions of personal thresholds can derive very different results at the aggregate level (Schelling, 1978). Threshold models can be used to formalize many social phenomena, including innovation, rumours and disease spreading (Rogers, 1995). However threshold models are usually extremely demanding with regard to the amount of information computed by individuals. When deciding what to do, individuals have a complete knowledge about what all others are doing. Granovetter (1978) suggests that "Social structure is one reason why the simple form of threshold models may not provide an adequate account of events. (…) The simple model makes an implicit assumption of complete connectedness which is often inappropriate: that each individual is responsive to the behaviour of all the others, regardless of the size or special or temporal dispersion of aggregation" (p. 1431).

Interesting variation of threshold models have been proposed to solve this limitation focusing on the study on the local effects in the personal networks of each individual (Valente, 1996). Here also it is assumed that individuals have to face a binary decision: either to adopt the innovation or not. Valente draws a distinction between external influence of the social system and internal influence of the personal network. While external influence affects individuals through mass media and cosmopolitan links, internal influence affects individuals through the personal network and according to the level of *exposure*. Personal exposure to the innovation is defined as the proportion of adopters in an individual's personal network at a given time. Like in other threshold models, individuals decide to adopt when a personal threshold is surpassed but, despite classical threshold models, it is also possible to distinguish whether the threshold is reached because of external or internal influence.

We also include a threshold mechanism in our innovation diffusion model in order to focus on social influence effects. When deciding whether to adopt or not, our consumers are affected by other adopters of their local networks if and only if the exposure in their personal network is higher than a given personal threshold. In our model we use a parameter in order to vary the horizon of the local network and we show that adoption dynamics vary considerably according to the definition of the local network. More precisely, we find that epidemic models (Dodds and Watts, 2005; Newman, 2002; Newman and Watts, 1999) can be used to predict the dissemination of products into a society of consumers when the local networks is relatively small (consumers observing only their friends) but they fail when the local network becomes slightly bigger (consumers observing also friends of friends).

## 3.4 The model

In our innovation diffusion model, agents are connected in a unique connected network. The nodes of the network are the consumers and each link between two nodes represents a relation of friendship between two consumers. 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 completely clustered and any information takes long time in order to travel from a node to another distant node. On the other hand, when the network is completely random, agents are not clustered at all and any information is spread to all other nodes within a very short time. However, in between these limits there is an area (the so called small world area) where the network is both still very clustered and information spreads very fast to all the clusters of the network (Amaral et al. 2000). Our model studies how the penetration of the product in the population of consumers is affected by the structure of this network.

The decision to adopt the innovation depends on an internal WOM process. Agents are involved in the WOM process if and only if they receive a message from some neighbour that has already adopted. This means that at each time step, each agent looks at its neighbours and it decides to adopt if and only if at least one of its neighbours has already adopted. If none of the neighbours has adopted yet and it has not decided before, then it does not decide either. When agent *i* is involved into the WOM process, the probability of agent *i* to adopt is:

$$a_{ij} = \mathrm{P}(U_{ij} \geq U_{i,MIN}) \tag{3.2}$$

where

$$U_{ij} = \beta_j \cdot x_i + (1 - \beta_j) \cdot y_i \tag{3.3}$$

$$y_i = \begin{cases} q_j \geq p_i \Rightarrow 1 \\ otherwise \Rightarrow 0 \end{cases} \tag{3.4}$$

$$x_i = \begin{cases} A_i \geq h_i \Rightarrow 1 \\ otherwise \Rightarrow 0 \end{cases} \tag{3.5}$$

$U_{ij}$ is the utility agent *i* has if it adopts innovation *j* and $U_{i,MIN}$ specifies *i*'s minimum utility requirement. The utility has two components that are threshold functions: individual preference $y_i$ and local social influence $x_i$ of *i*'s personal network; $\beta_j$ weights these two components and it represents how strong the social influence effect is in the market of product *j*. Markets with high $\beta_j$ are fashionable markets (e.g. clothes, electronic devises) markets whereas markets with low $\beta_j$ are more stable markets (e.g. groceries and durables). Concerning the individual part, $p_i$ is the individual preference of agent *i* and $q_j$ is the quality of the innovation *j*. Concerning the social influence part, $h_i$ is a personal threshold which determines the individual agent's susceptibility to its neighbours' behaviour and $A_i$ is the fraction of adopters in the $L^{th}$ order set of alters of agent *i* (personal network). Agents included in *i*'s personal network are called alters.

Direct friends are first alters (*L*=1), friends of friends are second alters (*L*=2) and so on. If the fraction of adopters in *i*'s personal network is higher than $h_i$ then the agent does feel social influence, otherwise it does not. The rationale of this formalization is the classical threshold mechanism of collective action: a consumer does not feel social pressure if just a few people around her behave in a particular way but once these people reach a certain number then she suddenly decide to change her mind and she behaves differently (Granovetter, 1978). Finally, diffusion is introduced in the population by external marketing effort $e_1$ that is assumed to be given and linear along the dynamics of the diffusion. During all the diffusion, any non-adopter agent is convinced to adopt with probability $e_1$. Once an agent has adopted, other agents connected to it through their personal network become also aware of the innovation and they are involved in the WOM process evaluating their utility according to (3.3).

In order to compare different speeds under different conditions, we report the variations in the $\rho$ indicator defined as

$$\rho = \frac{1}{T} \cdot \frac{\sum_{t=0}^{T} D(t)}{\sum_{t=0}^{T} f(t)} \tag{3.6}$$

where T indicates the total cycles of the simulations, *D(t)* is the cumulative function of adopters at time *t*, and *f(t)* is the number of adopters at time t (Arenas et al. 2000). The $\rho$ indicator allows us to compare different diffusions that reach the same number of adopters. In this model if the external marketing effort $e_1$ is positive, a complete diffusion always occurs. Then, because the external marketing effort $e_1$ is also constant during all the diffusion process, the speed of the diffusion is also a good indicator of how strong the WOM process is in the market.

In our analysis (section 3.5.3) we investigate how the speed of the diffusion changes when consumers have very similar or very different personal thresholds. Then we use a beta distribution in order to vary heterogeneity for the threshold $h_i$ of agents in the population[4]:

$$f(x) = \frac{x^{a-1}(1-x)^{b-1}}{\frac{(a-1)!(b-1)!}{(a+b+1)!}} \tag{3.7}$$

with mean $\mu = \frac{a}{a+b}$ and variance $\sigma^2 = \frac{ab}{(a+b)^2(a+b+1)}$. Notice that the beta distribution allows us to model the heterogeneity of the agent population from the homogeneous case (very high value for *a* and *b*) for which all agents have the approximately the same threshold until the uniform distribution (*a*=*b*=1) for which thresholds can vary randomly around the mean value.

## 3.5 Results

We implement our model as an agent based model. Here we present simulation results for a population of one thousand agents and where on average each agent has 4 neighbours. Each set of simulations contains twenty runs which are enough to let the averages and the standard deviations to converge. Here we report the average of the runs and when it is relevant the standard deviation of the runs.

### 3.5.1 Effects of social influence in different network structures

We begin investigating a very social susceptible society ($\beta_j$=1, $h_i$=0.3) representing a fashionable market where agents have a large personal network (*L*=2). Letting the external marketing effort being low and constant ($e_1$=0.001) we observe changes in $\rho$. In Figure 3.1, each point represents the speed of diffusion in a network for different degrees of randomness (*r*).

[4] The beta distribution (http://mathworld.wolfram.com/BetaDistribution.html) is defined between 0 and 1 and it allows specifying the degree of heterogeneity of random drawings (Garcia-Diaz and Witteloostuijn, 2005).

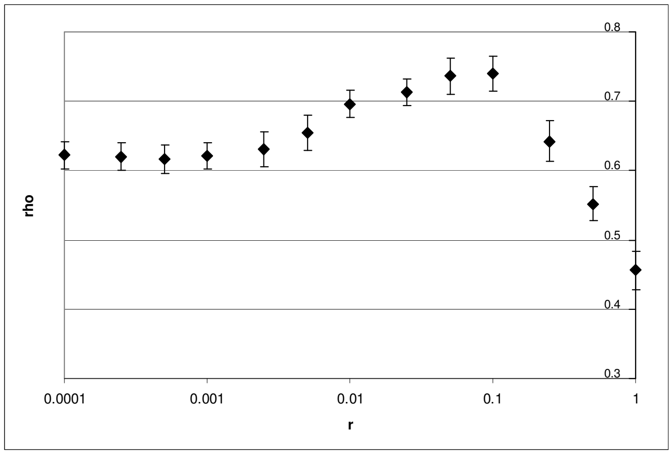


*Figure 3.1. The speed of diffusion $\rho$ (after 250 time steps) varying the degree of randomness in the network.*

When the network is almost completely clustered ($r$ = 0.0001), a group of innovators that start the diffusion can influence only local neighbours. Such influence is strong because the more clustered the group of adopters, the higher its influence on non-adopters neighbours (high exposure). Thus, the diffusion can travel along the network but it is slow: it cannot be spread in another distant region of the network. Consequently if some agents decide to not adopt the innovation, the WOM process dies and the only way to set the diffusion process again is by external influence. Then the time needed to convince all agents of the network to adopt is relatively large. The process changes when adding a little randomness into the network. Then shortcuts allow the innovation to emigrate in different parts of the network; diffusions can succeed easily and they spread very fast. Agents can see the spreading of diffusion in other clusters and they can import the fashion in their own cluster. At the same time, social influence is still very strong because the network is highly clustered. We observe the maximum values of $\rho$ for this small-world area. Finally, when the randomness becomes very high, social influence is dimmed. In random network, agents are not clustered, the portion of adopters in their neighbourhood is very low (low exposure). Consequently there is no social influence that presses them to adopt. During the initial part of the diffusion, innovators may decide to adopt only because of external influence. Because the external influence is low, then the critical mass is reached very late and, only then, the rest of the population will be suddenly convinced to adopt.

The parameter *L* plays an important role in this result. Figure 3.2 shows how the speed of diffusion varies in clustered, small-world and random networks if we vary L. When *L* is equal to 1, agents have a very small personal network because they are affected only by first alters' behaviour and when *L* is equal to 2, agents have a large personal network because they are affected both by first alters and by second alters' behaviour (see the social component of the utility function, i.e. (3.5)). When *L* is in between 1 and 2, then agents are affected by first alters' behaviour plus a proportion of second alters' behaviour as indicated in the decimals. (For example, when *L* is equal to 1.2, agents include in their personal network all first alters plus 20% of their second alters.)[5]

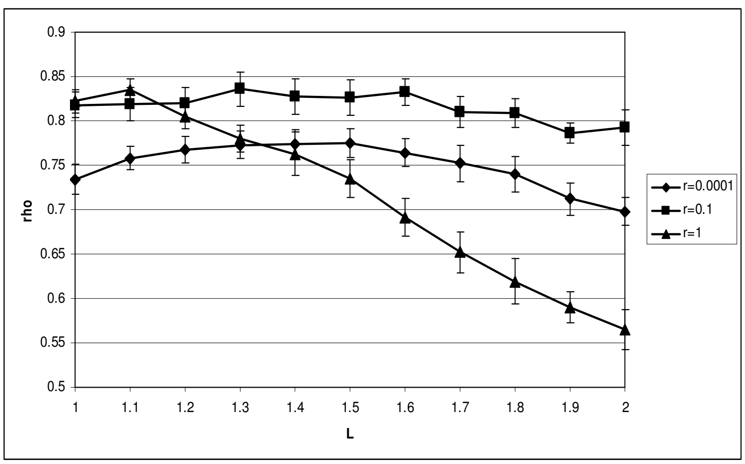


*Figure 3.2. The speed of diffusion $\rho$ (after 250 time steps) in different networks varying the horizon of agents' personal network.*

It is not trivial to foresee what happens to the speed of the diffusion when varying personal networks because a trade off exists between the social influence of the

[5] It is important to mention that varying the personal network does not directly affect the WOM process. What *L* does is to move the borders of personal networks when evaluating the social influence (3.5). For example, when *L*=2, an agent can observe a friend's friend behaviour and include it in the computation of its utility, but it cannot receive from it information about the innovation. In this way we can study the effect of *L* on the speed of diffusion without varying and altering the WOM process.

first alters and the social influence of the second alters. On the one hand, when the personal network of agent $i$ is small (for example $L$=1), just a few adopters in $i$'s personal network may represent a high percentage and $i$'s personal threshold can easily be reached. Then the innovation diffusion easily sets up and it can spread into the group. However in this case agent $i$ is affected only by those adopters that are very close and it may ignore clusters of adopters that are just 2 steps far. On the other hand, when $i$'s personal network is large (for example $L$=2), $i$ is affected by more friends' behaviours and just a few adopters into its group may not be sufficient to reach its personal threshold. However, having a larger social network allows $i$ to perceive the social influence of other clusters of adopters. Figure 3.2 shows what happens enlarging the personal network parameter ($L$). For the values of our simulation runs, the trade-off is quite balanced in clustered networks like the regular one ($r$=0.0001) and the small-world network ($r$=0.1). But the situation changes in random networks ($r$=1.0). Here, the absence of clusters does not permit the social influence to take place at all. Then, enlarging agents' personal network highly increases the time of the diffusion. Compared to the situation in which agents have a small personal network, the critical mass is reached later and it takes more time for the innovation to penetrate into the population.

### 3.5.2 Different markets

In the following set of simulations we control the robustness of our previous results investigating other values for the parameters $\beta_j$ and $h_i$. When we decrease (increase) the value of $\beta_j$, we simulate more (less) individualistic markets because agents decide more (less) according to their personal preferences. When we decrease (increase) the value of $h_i$, we simulate a more (less) turbulent market because agents are more (less) reactive to what other agents do in their personal networks. To investigate different kinds of market, from completely individualistic ($\beta_j$=0) to completely social susceptible ($\beta_j$=1), we let $L$=2.0, $h_i$=0.3 and we set $p_i$=[0,1] and $q_j$=0.5 assuming that agents have equal probability for positive or negative individual preference towards the innovation[6]. In

[6] For an analysis of different personal preferences on hits and flops of innovations, see Delre et al. (2007c).

Figure 3.3 we show results for different markets[7]. Here it can be seen that the effects of network structures decrease when markets are more individualistic. Decreasing the value of $\beta_j$, the value of $\rho$ depends less on the topology of the social network and, more importantly, when $\beta_j$=0.4 we see that diffusion in random networks is as fast as in small-world networks. This confirms the idea that epidemic models are suitable for individualistic markets but fail in markets with high social influence. In these fashionable markets diffusions are basically driven by social influence and having a clustered network is fundamental in order to spread the innovation fast.

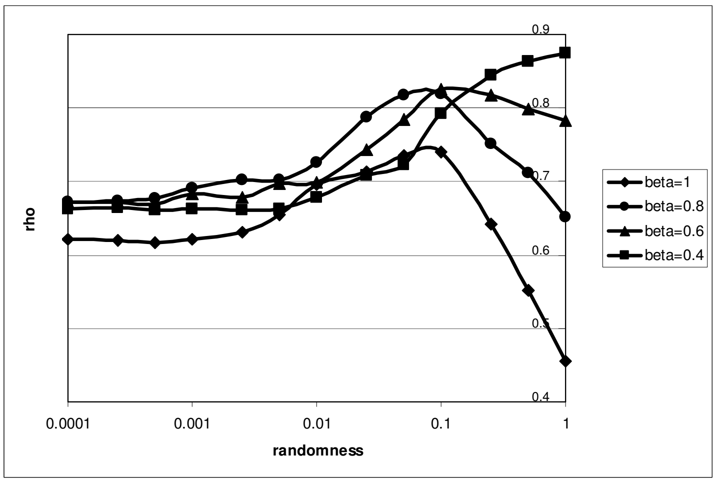


*Figure 3.3. The speed of diffusion $\rho$ (after 250 time steps) varying $\beta_j$*

Figure 3.4 shows diffusion dynamics in different turbulent markets. For these simulation runs, we set $\beta_j$ =1.0 and let the other parameters' values as before. However, especially in less turbulent markets, complete diffusions occurred after more than 300 time steps. Thus we collected values of $\rho$ after 400 time steps for each simulation run[8]. Obviously, the speed of the diffusion is lower when personal thresholds are higher.

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[7] For these runs at the end of the simulations the fraction of adopters in the population, *f*, (average among the 20 runs) varied depending on the value of $\beta_j$. For $\beta_j$=1.0, 0.998 < *f* < 1.0; for $\beta_j$=0.8, 0.903 < *f* < 0.917, for $\beta_j$=0.6, 0.782 < *f* < 0.837; for $\beta_j$=0.4, 0.674 < *f* < 0.746.

[8] Notice that the $\rho$ indicator is a mean of the speeds of the diffusion at each time step and varying the number of steps causes variations in $\rho$. However, as long as we compare simulation runs with the same time steps, differences among different simulation runs are not altered.

More interestingly, it can be noted that when agents have high personal thresholds, the small-world networks is not the fastest in spreading the diffusion anymore. The only thing that count here is how clustered the agents are: the more clustered they are, the more social influence adopters exert on non-adopters, the sooner the high personal threshold can be reached and the faster the diffusion disseminates.

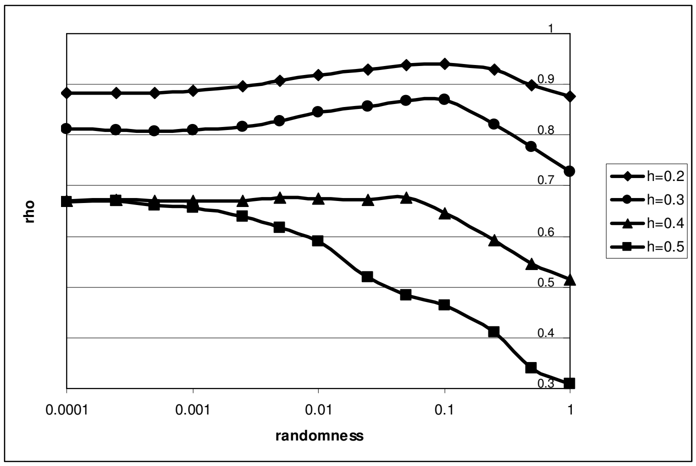


*Figure 3.4. The speed of diffusion $\rho$ (after 400 time steps) varying $h_i$*

### 3.5.3 Heterogeneous population of consumers

In the last set of simulations, we include heterogeneity in the populations. With the same parameter values as before ($L$=2, $\beta_j$=1.0, $r$=0.1) we observe a very high difference in the value of $\rho$ between the homogeneous case and the uniform distribution case (for $h_i$=0.3 we obtain $\rho$=0.792 and for $h_i$=[0, 0.6] we obtain $\rho$=0.892 after 250 time steps). Then we draw the value of $h_i$ from beta distributions (3.7) and we vary the values of $a$ and $b$ in order to maintain $\bar{h}$ (average of $h_i$) fixed and to obtain different variance in the population representing, in this way, different degrees of heterogeneity. In Figure 3.5, we show three sets of simulations for three different turbulent markets ($\bar{h}$=0.2; $\bar{h}$=0.3, $\bar{h}$=0.4). For each market we distribute agent's personal thresholds changing the variance into the population. In all three cases we find that more heterogeneity always causes a faster diffusion speed. When the populations become more heterogeneous there are more agents with lower and higher personal thresholds. Those that have a lower personal threshold are influenced sooner to adopt and they anticipate the ignition of the diffusion. Figure 3.6 shows five S curves of diffusion for different degrees of heterogeneity in the population of agents (homogeneous population, $h_i$=0.3; $a$=3, $b$=7, $\sigma^2$=0.138; $a$=6, $b$=14, $\sigma^2$=0.1; $a$=15, $b$=35, $\sigma^2$=0.064; uniform distribution, $h_i$=[0, 0.6]). It is clear how the time needed to complete the diffusion is much smaller as the population becomes more heterogeneous.

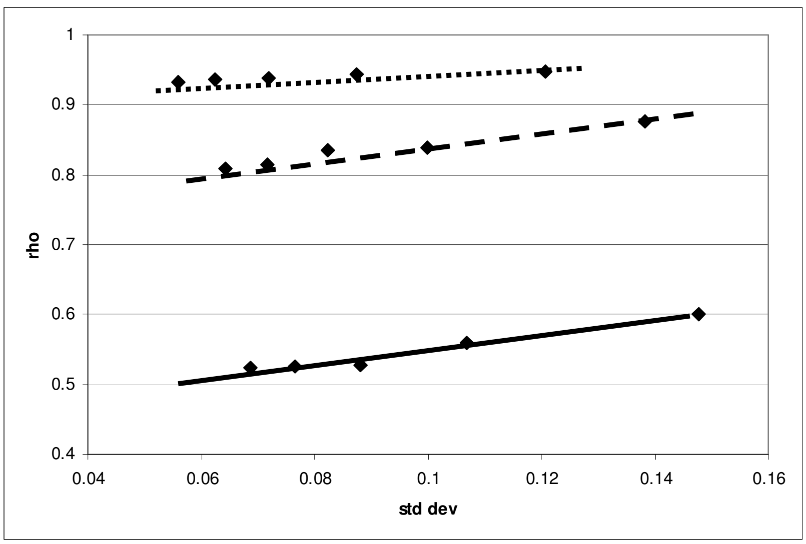


*Figure 3.5. The speed of diffusion $\rho$ (after 250 time steps) varying the degree of heterogeneity in the population. The continuous line indicates the trajectory for the points for which $\bar{h}$ =0.4, the continuous line for the points for which $\bar{h}$ =0.3 and the pointed line for the points for which $\bar{h}$ =0.2.*

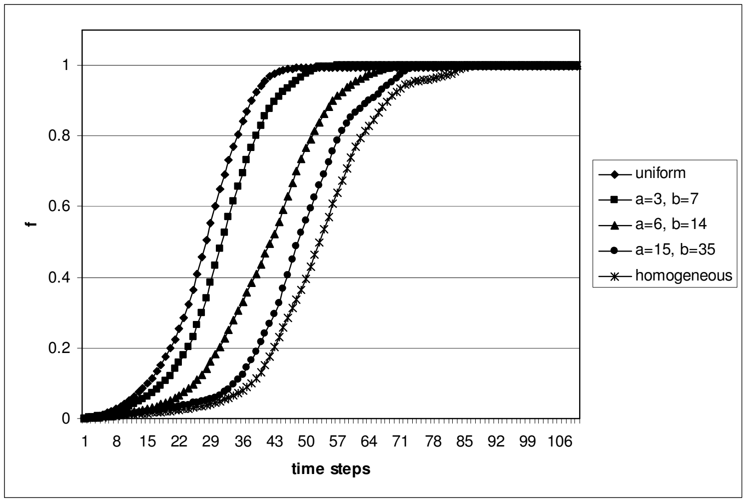


*Figure 3.6. The S curves of diffusion varying the degree of heterogeneity in the population*

## 3.6 Conclusions and Discussion

Epidemic models propose a new interesting methodology in order to study diffusion dynamics in biological, artificial and social networks (Dodds and Watts, 2005). The high relevance of these models stays in their generality which permits them to give insights and to be applicable in many different fields. Moreover, they may be highly interesting for economic and social phenomena because of their clear connection between micro specifications of individual characteristics and aggregate macro dynamics. There exists a population of nodes which are connected through links into a global network. The nodes are in a given state and diffusion dynamics are modelled as a penetration of a new state into the network: it can be a virus that flows because of infection and it can be a product that penetrated because of WOM. Epidemic models assume some individual characteristics like transmissibility (usually homogeneously into the population) and, either analytically or via computer simulations, they derive diffusion dynamics. However social contexts may need different assumptions about human behaviour and decision making. In this chapter we propose a new model in order to formalize innovation diffusions. Our model still belongs to the epidemic framework but it includes two strictly social concepts: (1) social influence in personal networks and (2) heterogeneity in decision-making. Simulation results show that in high social susceptible contexts the speed of the diffusion depends on how clustered groups are. Surprisingly, in high clustered networks innovations diffuse faster than in random networks. This is due to the fact that in clustered groups, individuals are exposed to more social influence and they may decide to adopt sooner. Especially in random networks, the dimension of personal networks also affects the diffusion: the bigger personal networks are, the slower the diffusion. Social influence explains this result. The bigger *i*'s personal network, the higher the number of adopters that are necessary in order to exert social influence on *i*. Then it takes longer for the diffusion to be set up. Finally we find that heterogeneity in consumer population helps the speed of the diffusion. In more heterogeneous population the critical mass is reached sooner than in homogeneous ones because there are more individuals that adopt at the beginning and they ignite the diffusion sooner.

The success of epidemic models in social studies depends on how adaptable these models are and how they are translated in social contexts that can include relevant behavioural and social aspects. Especially in contexts where the decisions are interconnected and interdependent it is necessary to reproduce more realistic decision-making rules. In fashionable markets, promotion and marketing strategies have to take these aspects into consideration. Because the success of the diffusion depends on the internal dynamics of groups of consumers, it is crucial to identify the right consumers (targeting those consumers that occupy strategic positions in the social networks) at the right time (finding the most efficient periods for promotion), in the right way (starting the diffusion with clustered, cohesive, visible groups that can influence others' behaviour).

# 4 Targeting and timing promotional activities for the takeoff of new products[9]

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

[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 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).

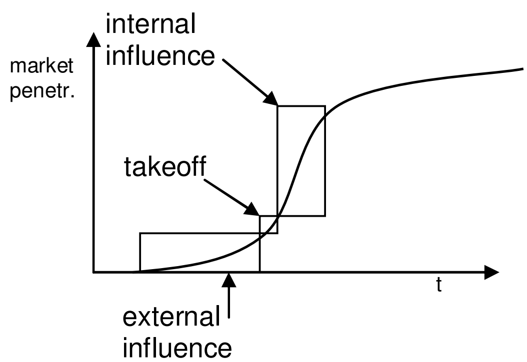


*Figure 4.1. The S-shaped curve of the diffusion.*

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:

$$U_{i,j} \geq U_{i,j,MIN} \tag{4.1}$$

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:

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

where

$$y_{i,j} = \begin{cases} q_j \geq p_i \Rightarrow 1 \\ otherwise \Rightarrow 0 \end{cases} \tag{4.3}$$

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

$$a_i = \frac{adopters_i}{adopters_i + non\_adopters_i} \tag{4.5}$$

$U_{i,j,MIN}$ 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, $p_i$ 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 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 $N$~(0.75, 0.01) to $N$~(0.8, 0.01) and $h_{i,j}$ varying from $N$~(0.35, 0.01) to $N$~(0.4, 0.01)) and brown good markets, such as TVs CDs, VCRs (with $\beta_{i,j}$ varying from $N$~(0.85, 0.01) to $N$~(0.9, 0.01) and $h_{i,j}$ varying from $N$~(0.2, 0.01) to $N$~(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 ($\beta_{i,j}$ = $N$~(0.9, 0.01), $h_{i,j}$ = $N$~(0.3, 0.01) and $e_2$ = 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 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:

$$g_t = ( S_t - S_{t-1} ) / S_t \tag{4.5}$$

$$v_t = S_t / N \tag{4.6}$$

$$T_t = (1 - v_t)^{\gamma} \tag{4.7}$$

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: $S_t = \sum_{i=5} s_{t-i}$ . 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.

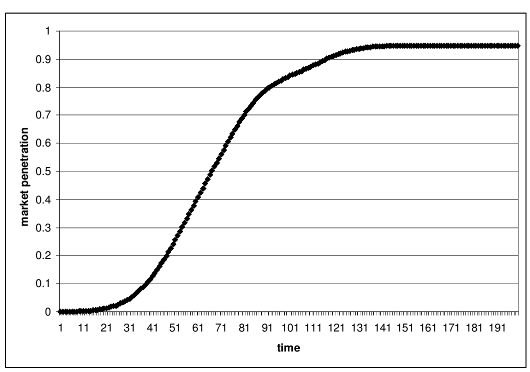

*Figure 4.2. The market penetration $v_t$ at each time step.*

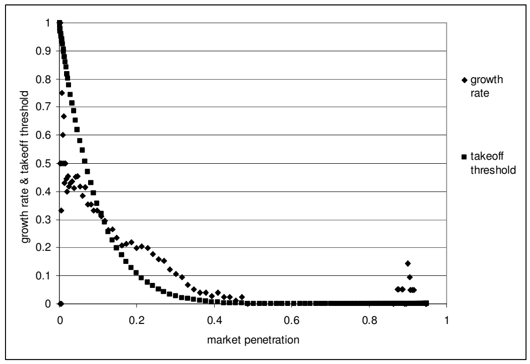


*Figure 4.3. The growth rate $g_t$ plotted against the market penetration $v_t$ and the threshold for the takeoff identification.*

## 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 $e_1$ 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.

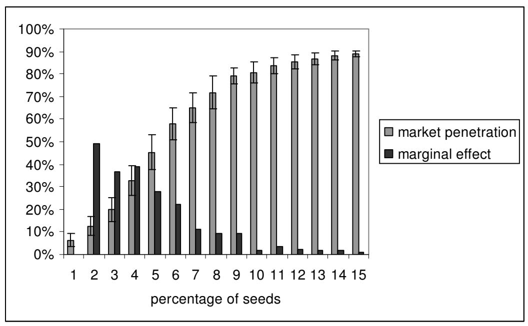


*Figure 4.4. Market penetration $v_t$ and marginal effect varying the number of seeds at moment of launch.*

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 ($e_1$ = 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.

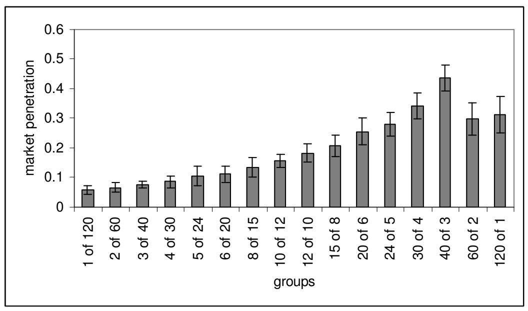


*Figure 4.5. The market penetration $v_t$ at the end of each simulation run balancing the throwing gravel strategy and the throwing rocks strategy.*

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 $e_1$ 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 $\beta_{i,j} = N\sim(0.9, 0.01)$ and $h_{i,j} = N\sim(0.4, 0.01)$. 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.

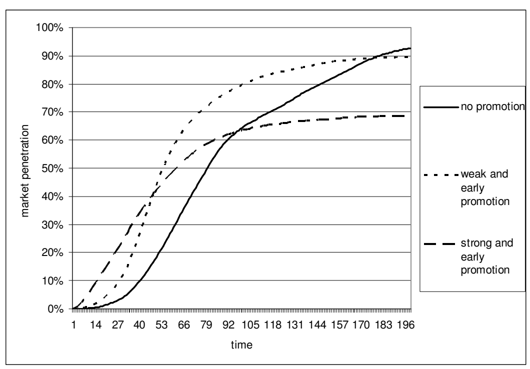


*Figure 4.6. Diffusion curves for different mass media campaigns (strong $e_2$ = 0.05 and weak $e_2$ = 0.005) placed at the beginning of the diffusion (from time step 0 until time step 10).*

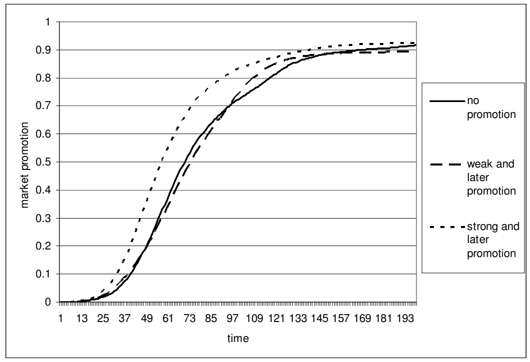


*Figure 4.7. Diffusion curves for different mass media campaigns (strong $e_2$ = 0.008 and weak $e_2$ = 0.002) placed at a later stage of the diffusion (from time step 20 until time step 50).*

### 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 $\beta_{i,j}$ and the $h_{i,j}$ parameters in the individual decision-making of the agents. When $\beta_{i,j}$ 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 $\beta_{i,j}$ is low and $h_{i,j}$ 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 ($v_t$ = 0.101) take off more quickly than white goods ($v_t$ = 0.136).

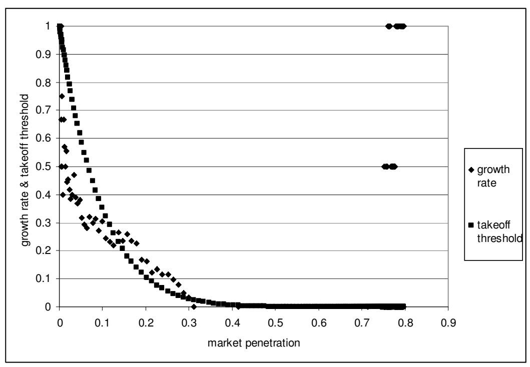


*Figure 4.8. Takeoff identification for white goods.*

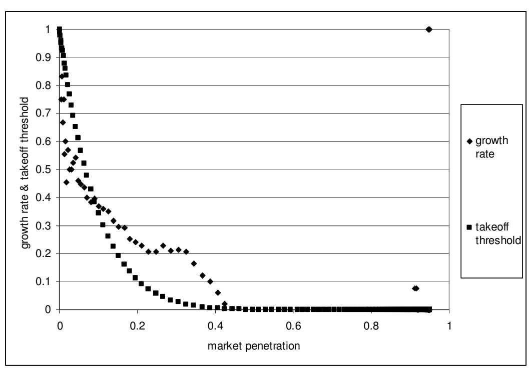


*Figure 4.9. Takeoff identification for brown goods.*

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.

| | 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 4.2
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 |

## 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 4.3

The parameters of the model, their values and the theoretical assumptions behind them

| Name | Parameter | Values | Theoretical assumptions |
|---|---|---|---|
| Simulation runs | | 20 | 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. |

| | | | |
|---|---|---|---|
| Time steps of the simulation run | | 500 | In all simulation runs, the system converges to a steady state where no more adoptions are 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* | $U_{i,j,MIN}$ | 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 she/he does not like it. |
| Takeoff threshold identification | $\gamma$ | From 8 until 12<br>Default value: 10 | 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 t 12. |
| Proportion of seeds (targeted consumers) | $e_1$ | Independent variable. | None. |

| | | | |
|---|---|---|---|
| Probability of messages of mass media campaigns to reach a consumer | $e_2$ | Independent variable.<br>Default value: 0.001<br>Strong mass media campaign: from 0.005 until 0.05<br>Weak mass media campaign: from 0.0005 until 0.002 | None. |
| Personal threshold sensibility to neighbours influence | $h_{i,j}$ | Independent variable<br>Default values for brown goods: *N*~(0.3, 0.01); default values for white goods: *N*~(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. (Alkemade and Castaldi, 2005; Granovetter and Song, 1986). |
| Weight of individual part and social part of an agent *i* in the utility function | $\beta_{i,j}$ | Independent variable<br>Default values for brown goods: *N*~(0.1, 0.01); default values for white goods: *N*~(0.25, 0.01) | 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). |

# 5 Simulating the Motion Picture Market: why do the hits take it all?[10]

Why are shares of the motion picture market so unequally distributed? Do the different qualities of the movies account for such an enormous difference in the market shares? Are mass media campaigns so effective to convince almost all movie visitors to see the same movies? Or are there social processes that affect the movie visitors' decision making and direct them to visit the same movies? In this chapter we propose an agent based model that formalizes the movie visitors' decision-making as the sum of individual utility of seeing the movie and social influence. Our agent based model distinguishes between quality messages that are connected with movies' characteristics and that determine the individual utility and advertising messages that create the buzz around the movie and that determine the social influence. In this way it is possible to study separately both the effect of quality and the effect of advertising on the gross revenues of movies. We use this model to generate time series of movie life cycles at the box office and then we compare these with time series of real movies. The results of several simulation experiments indicate that market shares become unequally distributed as observed in the real market only if the model takes into account strong social influences in the decision making of the movie goers. Moreover, only when advertising messages dominate quality messages, the life cycles of the simulated movies resemble those of real data. The success of movies depends more on the buzz generated around the movie than on the quality of the movie itself.

[10] The work of this chapter is based on a paper authored by Delre SA, Jager W, Bijmolt THA and Janssen MA, submitted and accepted at the Marketing Science Conference, 28-30 June 2007, in Singapore.

## 5.1 Introduction

During the last decade many studies have appeared in the marketing literature focusing on the motion picture market. Marketing scholars have recognized that the motion picture market is a very convenient environment where to conduct studies on marketing strategies. The price is fixed, the life cycle of the products terminates after a few weeks, and, most of all, data about the supply of the cinema market (i.e. production costs, marketing expenditures and revenues at the box office) are publicly available. Always more and more works have studied the antecedents of movie revenues such as advertising (Elberse and Anand, 2006; Prag and Casavant, 1994; Zufryden, 1996), reviews (Basuroy et al. 2003; Eliashberg and Shugan, 1997; Gemser et al. 2006), and movie stars (Albert, 1998; Basuroy et al. 2003; De Vany and Walls, 1999; Elberse, 2005; Ravid, 1999; Wallace et al. 1993). For a complete review of the state of the art, the reader is remanded to Eliashberg et al. (2006). However, one of the most striking puzzle remains unsolved. Movies revenues are distributed very unequally. Big mainstream movies like *Harry Potter*, *Spider Man*, *Star Trek*, are the real leaders of the market. When considering the most successful 250 movies of the year at the box office, 20% of the movies collected about 65% of the revenues. Figure 5.1 shows the distribution of movies' revenues in the USA market averaged for 6 years (from 2000 until 2005). They are ranked according to their revenue, from the first position until the 250th position[11]. It is evident that big successful movies take it all and all the rest have to accept very low shares of the market (Elberse and Oberholzer-Gee, 2006; Frank and Cook, 1995). For example, in 2002, when the mean of the revenues was $37,000,000, *Spider Man* (1st in rank) earned more than $400,000,000 and *The Piano Teacher* (250th in rank) earned $1,012,000. The variance of the distribution is very high and the mean is almost meaningless because it heavily depends on the upper tail. The most successful movies are the mainstream Hollywood ones. Nowadays they dominate the market and so it was in the previous years. The GINI coefficient measures how unequal the market shares of the market are. Its evolution from the '80s until the year 2006 shows that the market has always maintained this peculiar characteristic. After reaching picks of 0.65 during the '90s, in the last 5 years the GINI coefficient has stabilized around 0.6.

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[11] Movie data have been collected from http://www.variety.com, http://www.the-numbers.com, http://www.imdb.com and from the Motion Picture Association of America (MPAA), http://www.mpaa.org.

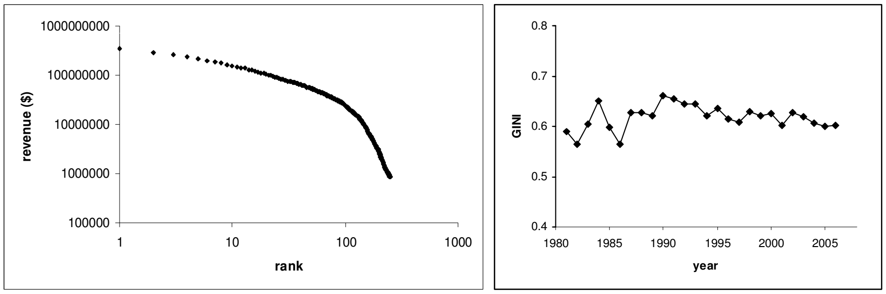


*Figure 5.1. Left graph: distribution of movies' revenues at the box office. Right graph: evolution of the GINI coefficient in the motion picture industry from 1981 until 2006.*

Many marketing scholars have immediately recognized this peculiarity of the market but they have hardly tried to tackle this issue. Especially the works that studied the supply part of the motion picture market and the efficacy of marketing strategies, have often avoided the issue. For example, when scholars aim at showing the effects of box office's drivers like marketing expenditures and newspaper reviews, it has become common practice to regress the independent variables on the logs of box office revenues (Basuroy et al. 2003; Eliashberg and Shugan, 1997; Gemser and De Haas, 2006; Gemser et al. 2006; Zufryden, 1996).

Why is that? The cinema market has recently flourished because it offers publicly available data that attract marketing scholars on studying the supply of the market but unfortunately there is also the other side of the coin: just a few works have studied the demand of the cinema market, those that go to the cinema, the movie consumers (Wieringa, 2006). Only sporadic attempts have been done to study the drivers of the consumer decision making and, besides their interesting findings, those works have not significantly initiated a relevant stream of research (Austin, 1986; Cuadrado and Frasquet, 1998; Eliashberg and Sawhney, 1994; Eliashberg et al. 2000; Möller and Karppinen, 1983; Tesser et al. 1987). Moreover a few works have attempted to link the way consumers decide to attend the movies and their convergence towards the same movies. (Banerjee, 1992; Bikhchandany et al. 1992; De Sornette et al. 2004; De Vany and Lee, 2001). These works have remained mostly theoretical models with minimal support from empirical data. One of the most important difficulties relates to the fact that the decisions of movie goers are very socially susceptible. They are highly affected both by the personal suggestions obtained by the friends that have already seen the movie and by the buzz that mass media create around the movie. It is not easy to track how social processes such as word-of-mouth (WOM) develop and to study how social influences such as imitation affect the final decision of movie goers. Only recently, thanks to the world-wide-web, these difficulties can be faced better. It becomes easier to create controlled settings where to track exchanges of information and opinions among a big number of consumers (Godes and Mayzlin, 2004; Salganik et al. 2006). Examples involving the movie market and in particular on how WOM affects the fruition of movies are Dellarocas et al. (2004); Liu (2006); Zhang et al. (2004).

Moreover the recent flourishing literature of the motion picture industry has often neglected the peculiar social aspects of the demand of this market and their consequences. This literature has adopted the classical concept of WOM from the traditional marketing literature on innovation diffusion (Mahajan et al. 2000). Here the WOM is seen as the messages that customers exchange about a new product, usually it is identified as the valuable advice of an innovator that has adopted a new product and does or does not recommend the product to other potential customers (internal influence). This classical WOM has always been seen as strongly in contrast with the mass media advertising messages (external influence) (Bass, 1969). Usually the good advice of a friend is much more valuable and convincing than a mass media advertisement. We believe that the distinction between advertisement and WOM is much looser for the cinema market. Here, movie goers often exchange messages before the movie is released and these messages do not focus on the quality of the movie but about the rumours around the movie. These rumours usually are not the valuable advice of friends that have seen the movie but, on the contrary, they are ignited by the huge mass media campaigns that studios producers conduct before launching a new film. Finally, while the importance of the classical WOM resides both in its volume and in its valence, what matters for the buzz of a movie is mainly its volume and not its valence. It is not uncommon to see that also negative messages contribute to the spread of the buzz around a new product (Sorensen and Rasmussen, 2004). Also Liu (2006) has clearly showed this effect. This study finds support to the fact that the volume of the messages movie visitors exchange is strongly related to the box office but the valence of these messages (positive vs negative advice) is not. Moreover this work shows that the most active exchange of messages among movie goers take place before and just when the movie is released. It seems that it is not important what customers say about the movie but how much they talk about it.

In this chapter we propose a new model of the movie consumer decision making. This is a simulation model implemented in an agent based model (Lusch and Tay, 2004). The agents' decisions of our model are affected both by the buzz that there is around the movie and by the quality of the movies. In this way the agent based model can generate movie life cycles. We conduct a sensitivity analysis which allows us to find the most realistic parameters' values and then we speculate about the meaning of these values. In order to rigorously conduct the sensitivity analysis of our simulation model we make use of the BOXMOD model (Sawhney and Eliashberg, 1996). We first fit BOXMOD with real data of the movie life cycles and then we fit BOXMOD with the simulated data. In this way we are able to find the most realistic parameters' values of our simulation model. This sensitivity analysis leads to the results of our work: (1) social influence is the most relevant cause of inequalities in the distribution of revenues at the box office, two times bigger than the buzz of the movies and seven times bigger than the quality perceived by the movie goers; (2) high successful movies display almost always the same typical life cycle: they obtain a very high revenues at the opening weekend and they decay rapidly in the following weeks. This is due to the strong pre-released mass media campaigns but, more importantly, to the fact that movie goers tend to exchange much more information about the buzz of the movies than about the movie characteristics; (3) given the total budgets for the movie and its fit with the movie goers' preferences, for studios producers it is more convenient to invest in advertising than in producing costs. Such a result remains also for higher levels of competitions. Summarizing our results it emerges a picture of the cinema market that it is much more focused on the entertainment consumption than on the art consumption.

This chapter is structured as follows: in section 5.2 we conduct an empirical analysis of the cinema market using the BOXMOD model. In section 5.3 we present our agent based model and in section 5.4 we perform the sensitivity analysis presenting our results. Finally, in section 5.5, we draw the implications of our findings and we discuss the limitations of our work.

## 5.2 The motion picture market

We have collected data for 291 movies, i.e., all movies that appeared at least once in the top 50 weekly classification between June 1st 2001 and May 31st 2002. We obtained data about the budgets of the movies: production costs, marketing expenditures; and about the movie life cycle at the box office: weekly box office, best position in the rankings and number of weeks in the cinema theatres.

The most common movie life cycle in our data set consists of the following pattern: high revenue at the first week followed by an exponential decay in the following weeks. This is usually associated to the so-called *wide release strategy* (Sawhney and Eliashberg, 1996). Distributors heavily promote the movie before its release and cinema theatres offer a high level of exhibition intensity (number of screens) at the beginning of the movie life cycle. During the following weeks the promotion decreases drastically and the exhibition intensity usually drops down following the demand. This particular pattern at the box office is due to the fact that many moviegoers visit the movie right when it is released at the opening week. Typical examples are *Spider Man*, *Artificial Intelligence*, *Jurassic Park* and many other mainstream movies that enter the top classification right at the first place and then they decay exponentially (Jedidi et al. 1998). Our data set contains also a number of *sleeper* movies. These movies usually use the so-called *platform release strategy*. This strategy suggests to open with relatively low advertisement and low exhibition intensity and, in case of positive response of the consumers, after one or more weeks, to increase the exhibition riding the positive WOM. Finally, the exhibition drops down following the demand.

Sawhney and Eliashberg (1996) introduce a simple model that is able to reproduce both these two different classes of movies: BOXMOD. BOXMOD is based on the individual decision making of movie goers and it has only three free parameters: individual time-to-decide parameter $\lambda$, individual time-to-act parameter $\gamma$ and potential number of adopters $n$. The model formalizes the cumulative distribution function (CDF) of adopters. This is given by the product of two different CDF: the CDF of movie goers deciding to go to the movie and the CDF of those that actually go to the movie. In (5.1) and (5.2) we report the specification of BOXMOD; the former formalizes the expected cumulative number of visitors and the latter formalizes the expected rate of adoption.

$$E[\,f(\,t\,)\,] = \frac{n}{\lambda - \gamma} \cdot \left[ (\lambda - \gamma) + \gamma e^{-\lambda t} - \lambda e^{-\gamma t} \right] \tag{5.1}$$

$$\frac{\partial E[\,f(\,t\,)\,]}{\partial t} = \frac{n\lambda\gamma}{\lambda - \gamma} \cdot \left[ e^{-\gamma t} - e^{-\lambda t} \right] \tag{5.2}$$

As also Sawhney and Eliashberg (1996) pointed out, it is important to notice that when the time-to-decide parameter $\lambda$ becomes extremely large (i.e., the average time-to-decide $1/\lambda$ decreases) the expected rate of adoption and the expected cumulative number of visitors become relatively fast approaching an exponential decay. This is why, the higher the value of $\lambda$, the faster the exponential decay. The model needs only 3 observations in order to make a prediction and it catches a fundamental distinction in the consumer decision making: after people have become aware of the movie, they first decide whether to go and then they take some time before actually going.

We fit BOXMOD with each one of the movie time series at the box office of our data set obtaining estimated values of $n$, $\lambda$ and $\gamma$ for each movie. Table 5.1 presents the results. Column 1 indicates the title of the movie, columns 2, 3 and 4 contain the estimates of BOXMOD, column 5 contains the degree of freedom (# weeks - 3), column 6 and 7 contain the real box office and the predicted box office (in millions of dollars) respectively, column 8 indicates the Mean Square Error (MSE) of BOXMOD and finally column 9 indicates the absolute error of the model ((predBO-actBO)/actBO) (Sawhney and Eliashberg, 1996). Then we conduct a meta-analysis on the estimated parameters and we present the results in Table 5.2.

Table 5.1

BOXMOD: Estimated parameters

| Title | n | gamma | lambda | df | act BO | pred BO | MSE | Abs err |
|---|---|---|---|---|---|---|---|---|
| O | 21.45 | 0.72 | 13.45 | 7 | 16.03 | 15.47 | 0.05 | 3.45% |
| 13 ghosts | 55.07 | 0.64 | 11.52 | 6 | 41.87 | 41.45 | 0.05 | 1.01% |
| 40 days and 40 nights | 43.61 | 0.58 | 2.61 | 9 | 37.95 | 38.79 | 0.12 | 2.20% |
| a beautiful mind | 175.39 | 0.27 | 0.29 | 20 | 170.74 | 172.49 | 3.22 | 1.03% |
| a night's tale | 62.54 | 0.56 | 2.03 | 9 | 56.13 | 57.05 | 0.49 | 1.63% |
| a walk to remember | 44.85 | 0.54 | 1.76 | 11 | 41.24 | 41.51 | 0.10 | 0.66% |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| about a boy | 42.71 | 0.56 | 1.25 | 6 | 40.68 | 39.95 | 0.39 | 1.80% |
| Ali | 56.28 | 0.88 | 11.00 | 4 | 38.18 | 38.09 | 0.11 | 0.24% |
| all about the benjamins | 34.89 | 0.70 | 19.15 | 8 | 25.51 | 24.98 | 0.01 | 2.09% |
| Along come a spider | 87.71 | 0.36 | 19.79 | 16 | 74.08 | 74.22 | 0.11 | 0.19% |

Table 5.2

Meta analysis: correlations among the BOXMOD estimates and the movies' variables

| | n | gamma | lambda | ln_lambda | prod_budget | adv_budget | # weeks | best_pos |
|---|---|---|---|---|---|---|---|---|
| gamma | 0.026 | | | | | | | |
| | (0.679) | | | | | | | |
| lambda | 0.349** | -0.079 | | | | | | |
| | (<0.01) | (0.211) | | | | | | |
| ln_lambda | 0.417** | 0.071 | .842** | | | | | |
| | (<0.01) | 0.260 | (<0.01) | | | | | |
| prod_budget | 0.719** | 0.032 | 0.287** | 0.372** | | | | |
| | (<0.01) | (0.660) | (<0.01) | (<0.01) | | | | |
| adv_budget | 0.728** | 0.072 | 0.054 | 0.256 | 0.804** | | | |
| | (<0.01) | (0.714) | (0.784) | 0.189 | (<0.01) | | | |
| # weeks | 0.217** | -0.254** | 0.054 | -0.247** | 0.213 | 0.403* | | |
| | (0.01) | (0.001) | (0.39) | (<0.01) | (0.03) | (0.034) | | |
| best_pos | 0.522** | -0.384** | -0.266** | -0.434** | -0.494** | -0.598** | 0.18** | |
| | (<0.01) | (<0.01) | (<0.01) | (<0.01) | (<0.01) | (0.001) | (0.004) | |
| act_BO | 0.994** | -0.037 | 0.299** | 0.376** | 0.702** | 0.709** | 0.245** | -0.510** |
| | (<0.01) | (0.562) | (<0.01) | (<0.01) | (<0.01) | (<0.01) | (<0.01) | (<0.01) |

*Note. * Significant at the 0.1 level; ** Significant at the 0.05 level.*

Table 5.2 shows that $\lambda$ strongly correlates with $n$, the best position, the number of weeks in the theatres and the real box office. Because the increases of the $\lambda$ estimates exponentially decrease their effect on the decay of the revenues, we also checked the correlations between $n$ and $ln(\lambda)$. We can notice that the coefficient for this correlation is lightly stronger than the correlation between $n$ and $\lambda$. Reminding the reader to the fact that a higher $\lambda$ means lower time-to-decide and faster decay of the box office, we observe that a positive correlation between $ln(\lambda)$ and $n$ means that the more successful movies usually show a faster decay at the box office. This is in line with many empirical works that have shown how big hit movies, usually mainstream Hollywood movies, almost always enter the market at the first place of the classification and then they decay quickly (Ainslie et al. 2005; Elberse and Anand, 2006; Jedidi et al. 1998; Sawhney and Eliashberg, 1996). However this evidence is in contrast with another line of research that views the market as extremely uncertain and that suggests that usually only when movies are able to *build they own legs* (i.e., positive WOM) and only when they can stay longer in the theatres, they manage to obtain high revenues at the box office (De Vany and Lee, 2001). Finally it is interesting to notice that $\gamma$ correlates only with best position and the number of weeks in the theatres but quite surprisingly it does not correlate either with $n$ or with the real box office. This indicates that movies that are easily available to movie goers (e.g., they have a high number of screens) tend to be higher in the classification, to remain less in the theatres but they do not obtain higher revenues.

## 5.3 The simulated motion picture market

Here below we present the complete simulation model of the motion picture market. It is an agent based model and the core of the model is the individual decision-making of movie goers. After agent $i$ is informed about movies according to (5.3) or (5.4), it evaluates the expected utilities of these movies according to (5.5). Then it visits the movie that has the highest expected utility and finally, seeing the movie, it experiences a level of satisfaction as formalized in (5.8).

$$BUZZ_{j0} = e^{-\frac{\omega_1}{M_j}} \tag{5.3}$$

$$BUZZ_{jt} = BUZZ_{j,t-1} + \delta_1 \cdot \left( Box_{j,t-1} / N - BUZZ_{j,t-1} \right) \tag{5.4}$$

$BUZZ_{jt}$ is the buzz of movie $j$ at time $t$. It can be interpreted as the sum of all promotion messages and rumours about the movie $j$ at time $t$ and it formalizes the probability that agent $i$ is informed about movie $j$ at time $t$. As specified in (5.3), at time 0, just when the movie is released into the cinema theatres, $BUZZ_{j0}$ depends on the advertisement budget of movie $j$ $M_j$, and on $\omega_1$ which is a free parameter of the model and it indicates how strong the informative effect of the advertising budget is on the agents. The shape of the function is in line with findings that showed diminishing returns between advertisement expenses and its effects on consumer's behaviours (Hanssens et al. 2001; Leeflang et al. 2000; Lilien and Rangaswamy, 2003). Moreover the initial low increase of $BUZZ_{j0}$ for very low values of $M_j$ fully represents the fact that an insufficient amount of money spent in advertising may result in an almost inconclusive campaign. After the movie is released, $BUZZ_{jt}$ evolves as specified in (5.4). $Box_{j,t-1}$ is the box office movie *j* has obtained at the previous time step, *N* is the total number of agents and $\delta_1$ is a free parameter. This formulation assumes that $BUZZ_{jt}$ evolves according to the success that the movie *j* has at the box office: the more the success a movie gains after its release, the higher its buzz becomes. Here $\delta_1$ formalizes the retention rate of advertisement messages and it determines how fast the evolution toward the actual box office of the movie is. On the one hand, if $\delta_1$ is very low then agents retain the effects of advertisement budget longer and they are less affected by the results that the movie has at the box office; on the other hand, if $\delta_1$ is very high then agents forget sooner the effects of the initial campaign and they are more affected by the results that the movie has at the box office. For similar examples of formalizations and estimations of advertisement retention rates, the reader can refer to Hanssens et al. (2001) and to Leeflang et al. (1992).

$$E[U_{ijt}] = \beta_i \cdot y_{ijt} + (1-\beta_i) \cdot x_{jt} \tag{5.5}$$

$$y_{ijt} = f(WPQ_{jt}, m_j, p_i) = WPQ_{jt} \cdot (1 - | m_j - p_i |) \tag{5.6}$$

$$x_{jt} = f(N, TotBox_t, BUZZ_{jt}) = \frac{TotBox_t}{N} + BUZZ_{jt} \cdot \left(1 - \frac{TotBox_t}{N}\right) \tag{5.7}$$

$$Sat_i = [1 - |m_j - p_i|] \tag{5.8}$$

$$WPQ_{j0} = e^{-\frac{\omega_2}{C_j}} \tag{5.9}$$

$$WPQ_{jt} = WPQ_{j,t-1} + \delta_2 \cdot (< Sat_{j,t-1} > - WPQ_{j,t-1}) \tag{5.10}$$

After agent *i* has been informed about movie *j*, it evaluates it according to (5.5). The expected utility $E[U_{ijt}]$ is given by two components: an individual expected utility and a social expected utility. The two components are weighted by $\beta_i$ which indicates how much agent *i* decides according to its own preferences or how much it is affected by other agents' decisions. The expected individual utility (5.6) is driven by movie characteristics $m_j$, agents' preferences $p_i$ and the wording perceived quality $WPQ_{jt}$. Both movie characteristics $m_j$ and agents' preferences $p_i$ are assumed to vary from 0 to 1. Then $1-|m_j - p_i|$ represents how much the movie features match the agent's preferences. The $WPQ_{jt}$ formalizes the evolution of the movie quality, as perceived by the audience, from its exordium in the cinema theatres until the end of its life cycle. At the moment of the launch, $WPQ_{j0}$ is a simple function of the production budget $C_j$ in a similar way that $BUZZ_{j0}$ is function of the advertising budget $M_j$ (5.9). After the movie arrives into the theatres, its quality discloses and it converges towards the satisfaction of the public (5.10). Here $<Sat_{j,t-1}>$ is the average satisfaction obtained by those agents that have already seen movie *j* and $\delta_2$ is a free parameter that determines how fast the $WPQ_{jt}$ converges towards it. It is evident how $\delta_1$ and $\delta_2$ play similar roles in different contexts: while $\delta_1$ tells how fast the buzz spreads into the population, $\delta_2$ tells how fast the information about the quality of the movie reaches the public.

The expected social utility depends on the social influence that other agents have on agent *i*. This is driven both by those that have already seen the movie ($TotBox_{jt} / N$), where $TotBox_{jt}$ is the total number of agents that have already seen the movie, and by those that may want to see it but they have not seen it yet ($BUZZ_{jt}\ (1-TotBox_{jt} / N)$). In other words, the social influence exerted on agent *i* is given by the probability that an agent has already seen movie *j* times the probability that an agent that has not seen movie *j* is informed about it. For a similar formalization of social influence, see Hidalgo et al. (2006). Finally $\sigma$ indicates how the total budget of each movie is split in advertising budget $M_j$ and production budget $C_j$. Figure 5.2 summarizes the entire model.

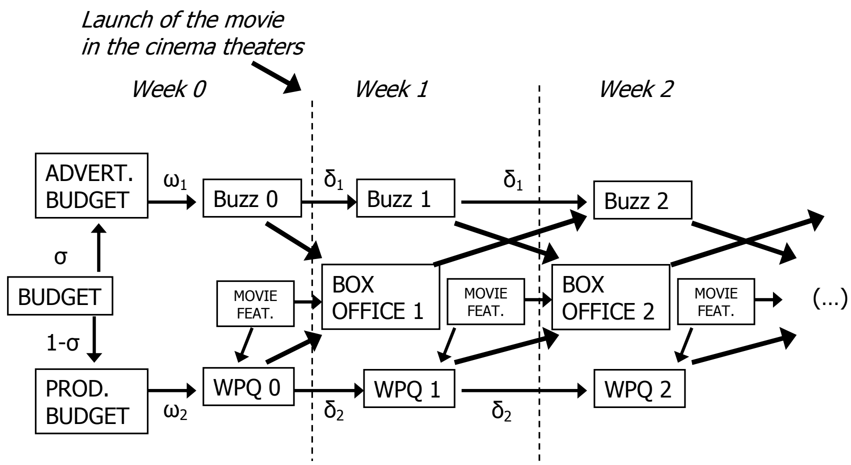


*Figure 5.2. The formalization of the agent based model*

The simulation model described above is implemented in a realistic USA cinema market context. Each time step of the simulation corresponds to a week and at each time step new movies are introduced into the market. The model generates 480 movies per year, for 3 years. We select only the 480 movies that enter the market during the second year and we record their complete life cycle at the box office. In this way we avoid initial and final simulation distortions: both we include the competition of movies that are introduced in the first year and last in the second year, and we complete life cycles of movies that are introduced in the second year and last until the third year. Moreover, the famous season effect (Ainslie et al. 2005; Elberse and Eliashberg, 2003; Vogel, 1998) is taken into account: the number of agents that are involved into the decision making process at each time step is proportional to the attendance observed in the real market and the number of movies released each week is also proportional to the attendance. Finally we draw the total budget of each movie from our data set (see section 5.2) and we obtained the values of $M_j$ and $C_j$ setting $\sigma$ =35% as it is common practice by big studios that usually both produce and distribute the movies (Motion Picture American Association -MPAA- U.S. Theatrical Marketing Statistics, 2006).

A very important feature of this model is the distinction between the buzz and the wording perceived quality of movies. We adopt this distinction in order to separate two different concepts: the buzz formalizes all rumours about the movie and the wording perceived quality formalizes the quality of the movie as perceived by the audience. While the former is mainly ignited by promotion messages and it evolves according to the box office, the latter is based on movie characteristics and it evolves according to the satisfaction of the customers that see the movie. In our model we adopt this distinction in order to study separately the effects of the buzz and of the movie characteristics.

## 5.4 Findings

Our simulation model is able to generate movie life cycles as in the real cinema market and consequently a distribution of revenues at the box office. But how do these life cycles change for different values of the free parameters? And what is their effect on the final revenues of the movies? Given our model, what are the *true* parameters that are able to generate a simulation market that is the most realistic one? We first confine plausible parameter values according to theoretical foundations and then we conduct a sensitivity analysis of our model. In order to conduct a rigorous analysis we fit the obtained simulated data in BOXMOD as we did in section 5.2 with the real data. Our first simulation runs investigate 5 free parameters of the model. These values are combined into a factorial experimental design that generates 108 simulation markets (Table 5.3). We do not make strict assumptions about social influence and we let $\beta_i$ to vary quite extensively (low, medium and high social influence) because we find that social influence exerted by others' behaviours can largely vary (Austin, 1986; Möller and Karppinen, 1983). About the advertising effects we assume that the advertising budgets mainly affects the awareness of the agents (Elberse and Anand, 2006) and that the relation between advertising budget and awareness is s-shaped and log-reciprocal (Lilien and Rangaswamy, 2003). The strength of the advertising budget on $BUZZ_{j0}$ is determined by $\omega_1$. Because we draw real advertising values from our data set and we plug them in $M_j$, it is plausible to use values around the average advertising expenditure. Because the average advertising expenditure reported by MPAA in 2000 and 2001 is around \$27 millions, we decide to investigate the cases of low advertising effect ($\omega_1$=50 millions) and high advertising effect ($\omega_1$=10 millions). We adopt an analogous formalization for $WPQ_{j0}$ which depends on $C_j$ and on $\omega_2$. In this case the average production budget is around \$50 millions and we study the cases of weak effect ($\omega_2$=100 millions) and strong effect ($\omega_2$=10 millions) on the wording perceived quality $WPQ_{j0}$. Finally, concerning the retention rates, $\delta_1$ and $\delta_2$, we assume that the maximum impact of advertising is when the movie is just released and that it declines to zero according to a constant fraction (Hanssen et al. 2001, p. 145-146; Palda, 1964). While the average advertising retention rate for frequently purchased goods and monthly data is about 0.5 (Assmus et al. 1984), it is not easy to figure out the retention rate for movies. On the one hand the retention rate can be higher (customers forget soon the advertising) because the competition is usually high and the typical movie life cycles is extremely fast. On the other hand the retention rate can be lower (customer forget later the advertising) because costumers are usually more involved in movies than in other product. Thus we decide to investigate the parameter space around the medium and most common value: 0.3 stays for a high retention of the advertising, 0.5 stays for a medium retention and 0.7 stays for a low retention. We adopt a similar formalization also for the evolution of $WPQ_{jt}$ where $\delta_2$ determines the speed of the evolution from the initial wording perceived quality $WPQ_{j0}$ until the actual satisfaction of the agents. Although we have not found previous similar formalizations for the $WPQ_{jt}$, we maintain that this formalization is plausible and it is also convenient because it permits a comparison between the retention rate of advertising and the retention rate of quality messages. Consequently for $\delta_2$ we decide to investigate the same parameter space: 0.3 stays for a strong retention of initial quality message, 0.5 stays for a medium retention and 0.7 stays for a low retention.

Table 5.3

Experimental design

| Parameter | Value | Interpretation |
|---|---|---|
| $\beta_i$ | 0.25 | Low social influence |
| | 0.5 | Medium social influence |
| | 0.75 | High social influence |
| $\omega_1$ | 10 millions | Strong informative effects of advertising budget on movie goers |

| | | |
|---|---|---|
| | 50 millions | Weak informative effects of advertising budget on movie goers |
| $\omega_2$ | 10 millions | Strong effects of production budget on the quality perceived by movie goers |
| | 100 millions | Weak effects of production budget on the quality perceived by movie goers |
| $\delta_1$ | 0.3 | High retention rate of advertising messages |
| | 0.5 | Medium retention rate of advertising messages |
| | 0.7 | Low retention rate of advertising messages |
| $\delta_2$ | 0.3 | High retention rate of quality messages |
| | 0.5 | Medium retention rate of quality messages |
| | 0.7 | Low retention rate of quality messages |

For each simulation run we collect the first 200 movies at the box office (out of the 480 movies of the second simulated year) and we study how their revenues changes for the different parameters' setting of the experimental design. In particular, we focus our attention on the GINI coefficient *g*. Table 5.4 clearly indicates that *g* highly depends on the level of social influence consumers decide with. As we mentioned before, the real GINI coefficient of the cinema market is about 0.6. In our simulation markets, we obtain that for $\overline{\beta}$ =0.25 the average *g* is 0.535, for $\overline{\beta}$ =0.5 the average *g* is 0.617 and for $\overline{\beta}$ =0.75 the average *g* is 0.663. In Table 5.4 we also investigate how *g* varies according to other parameters' values. Besides the social influence, that is the most influential determinant of market inequalities, we find also that *g* varies with $\delta_1$, $\delta_2$, $\omega_1$ and $\omega_2$. In order to compare these effects, we regress the Gini coefficient *g* on $\overline{\beta}$, $\omega_1$, $\omega_2$ and $\delta_2 - \delta_1$ and we present the results in Table 5.5 and Figure 5.3. When the retention rates of $BUZZ_{jt}$ is stronger than the retention rate of $WPQ_{jt}$ (i.e. $\delta_2 < \delta_1$ and consequently $\delta_2 - \delta_1$ >0), agents need more time to discover the movies' qualities, it is more difficult to find the movies that match their preferences and their behaviours converge towards movies that are visited by the other agents. Also $\omega_1$ and $\omega_2$ contribute to the inequalities at the box offices. In these cases, the stronger the informative effect of advertisement and the stronger the effect of production budget on the initial wording perceived quality are (lower values of $\omega_1$ and $\omega_2$), the lower *g* becomes. The former effect is due to the fact that when $\omega_1$ is low, agents are informed about more movies and they can decide among a more variegate set of movie characteristics. In this way they can find movies that most adhere to their preference and this contrasts the social influence effect. The latter effect is due to the fact that when $\omega_2$ is low, there are more movies that are considered of higher quality and this again contrasts the social influence effect.

Table 5.4

The variations of market inequalities

| Parameter | Value | GINI coefficient (average) | GINI coefficient (stand. dev.) |
|---|---|---|---|
| $\overline{\beta}$ | 0.25 | 0.535 | 0.047 |
| | 0.5 | 0.617 | 0.042 |
| | 0.75 | 0.663 | 0.041 |
| $\omega_1$ | 10 millions | 0.598 | 0.089 |
| | 50 millions | 0.612 | 0.036 |
| $\omega_2$ | 10 millions | 0.588 | 0.065 |
| | 100 millions | 0.622 | 0.067 |
| $\delta_1$ | 0.3 | 0.635 | 0.069 |
| | 0.5 | 0.597 | 0.066 |
| | 0.7 | 0.583 | 0.061 |
| $\delta_2$ | 0.3 | 0.615 | 0.065 |
| | 0.5 | 0.604 | 0.069 |
| | 0.7 | 0.597 | 0.072 |

Table 5.5

Regression analysis. The drivers of market inequalities

| Parameter | Coefficient | t value | Sig. |
|---|---|---|---|
| Constant | | 30.116 | <.001 |
| $\overline{\beta}$ | .766 | 16.010 | <.001 |
| $\omega_1$ | .104 | 1.863 | .065 |
| $\omega_2$ | .250 | 4.491 | <.001 |
| $\delta_2 - \delta_1$ | .143 | 2.565 | .012 |

*Note. R Square=.680*

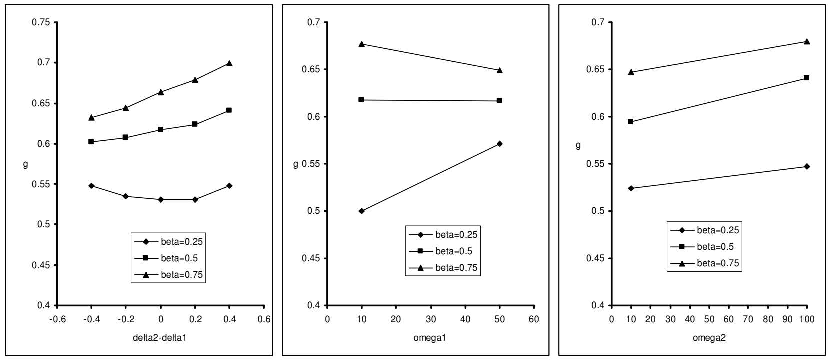


*Figure 5.3. How the market inequalities depend on $\overline{\beta}$, $\omega_1$, $\omega_2$ and ($\delta_2 - \delta_1$).*

Our agent based model allows us to generate complete movie life cycles at the box office. We can control for which parameters' setting the simulated movies life cycles adhere to the real ones. In order to do so, we fit BOXMOD with the simulated movies and then, as we did with the real market, we conduct a meta-analysis for each parameters' setting. We exclude from the analysis the simulated movies that did not converge to estimates of $n$, $\gamma$ and $\lambda$, the movies whose life cycles last less than 4 weeks and the movies whose absolute error in the estimation is higher than 15%. BOXMOD is highly robust to the changes in the parameters' setting. In fact, more than 80% of the movies remain after the exclusions. More precisely, for $\overline{\beta}$=0.25, 88%of the movies remain; for $\overline{\beta}$=0.5, 84% remain and for $\overline{\beta}$=0.75, 73% remain. These differences are mainly due to the length of the movies' life cycles. For $\overline{\beta}$=0.25 the average life cycle lasts 16 weeks, for $\overline{\beta}$=0.5 it lasts 13 weeks, and for $\overline{\beta}$=0.75 it lasts 11 weeks. This last simulation results indicate that, although a certain degree of social influence is necessary in order to explain the high inequalities of the revenues, an excessive degree of social influence would create unrealistically short movies' life cycles.

The comparison of the simulated movies life cycles with the real ones leads to further results. In the real data we have noticed the surprising positive correlation between $n$ and $ln(\lambda)$. Fitting BOXMOD with our simulation data allows us to look for the parameters' setting that generates such a correlation. As we have done in section 5.2

with the real data, here we fit BOXMOD with our simulated data, we transform the correlations using the Fisher Transformation and in Table 5.6 and in Figure 5.4 we show how the average correlation between *n* and *ln(λ)* varies depending on $\delta_2 - \delta_1$, $\omega_1$ and $\omega_2$ for different levels of $\overline{\beta}$. On the left graph of Figure 5.4 we show how the correlation between *n* and *ln(λ)* varies according to the difference between $\delta_2$ and $\delta_1$. When $\delta_2 << \delta_1$ ($\delta_2 - \delta_1$ =-0.40), agents mainly exchange information about $WPQ_{jt}$ and they are only marginally affected by $BUZZ_{jt}$. On the opposite extreme, when $\delta_2 >> \delta_1$ ($\delta_2 - \delta_1$ =0.40), the agents are more affected by $BUZZ_{jt}$ than $WPQ_{jt}$. When the simulated cinema market is mainly dominated by quality information ($\delta_2 - \delta_1$ =-0.40) we do not find any positive correlation between *n* and *ln(λ)*. In this case, the life cycles of the most successful movies still display a typical exponentially decay but the decay is not positively correlated with the box office. On the other hand, such a correlation arises and it grows up when agents are increasingly more affected by $BUZZ_{jt}$ than $WPQ_{jt}$. In these cases, the most successful movies are those that manage to bring as many potential visitors as possible at the opening weekend. Those movies ignite a higher buzz before their release, they recoup their costs faster and after that they also decay faster. Stated differently, only when the effect of $BUZZ_{jt}$ is superior to the effect of $WPQ_{jt}$, we obtain a simulated realistic market. The central graph and the right graph of Figure 5.4 confirm this result. The correlation between *n* and *ln(λ)* increases when the effects of the advertising budget are strong (low values of $\omega_1$) and when the effects of the production budget are weak (high values of $\omega_2$).

Table 5.6

Regression analysis. How the correlation between *N* and *ln(λ)* is affects by $\overline{\beta}$, $\omega_1$, $\omega_2$ and $\delta_2 - \delta_1$

| Parameter | Coefficient | t value | Sig. |
|---|---|---|---|
| Constant | | 12.276 | <.001 |
| $\overline{\beta}$ | -.445 | -7.043 | <.001 |
| $\omega_1$ | -.541 | -8.554 | <.001 |

| | | | |
|---|---|---|---|
| $\omega_2$ | .118 | 1.874 | .064 |
| $\delta_2 - \delta_1$ | .289 | 4.568 | <.001 |

*Note. R Square=.588*

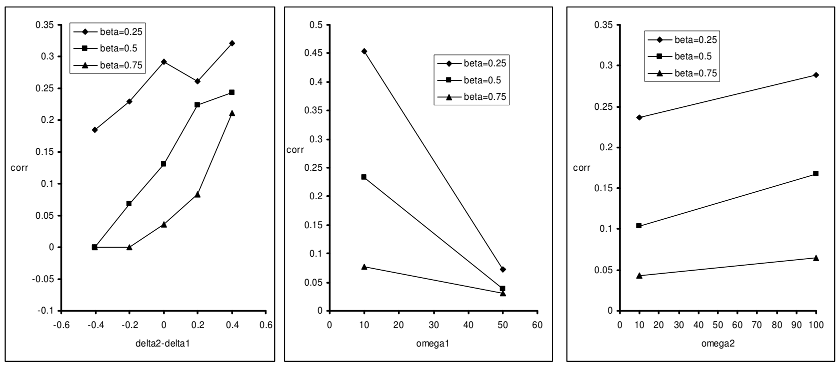


*Figure 5.4. How the correlation between N and ln(λ) varies according to* $\overline{\beta}$ , $\omega_1$ , $\omega_2$ *and* $\delta_2 - \delta_1$ .

The previous simulation runs have mainly focused on the demand of the motion picture market. We have investigated the movie goers characteristics that can cause the observed market outcomes, namely the unequal distribution of revenues and the typical exponential decay of the most successful movies. However we can also use our agent based model in order to focus on the other side of the market: the supply. In particular, we can test for different marketing strategies of the movie producers. In the previous simulation runs, we have taken the supply of the market as given and we have assumed that the studios that produce the movies divide the movie budgets with a simple split as commonly observed in reality. There we have set $\sigma$ =35% such that 65% of the total budget is used for production costs and 35% of the total budget is used for advertising costs. Here we reverse our analysis: we take the demand of the market as given and we study the efficiency of the supply: in particular, we investigate how different studios may use different strategies in dividing the total budget into production costs and advertising costs. How studios should split their budget? Is it better to invest in advertising that increments the awareness and the buzz around the movie or in production costs that guarantee a high level of quality? Stated differently, given the behaviour of the movie goers and an extra dollar in the total budget, is it more convenient to use it for advertising or production costs? First we set the model with realistic parameters' values according to the results of the previous simulations ($\overline{\beta}$ = 0.5; $\delta_1$ = 0.7; $\delta_2$ = 0.5; $\omega_1$ = 10 millions and $\omega_2$ = 100 millions) and then we simulate the supply of the market with movies whose budgets are differently split. We assume that movies can uniformly vary from a 90-10 split (production costs and advertising costs, respectively) to a 50-50 split ($\sigma_j$ = [10%, 50%]). Then we observe the performances of the different strategies checking how the movies' box offices depend on the divisions of the budget. We conduct this analysis simulating different levels of competition (i.e. more or less movies introduced into the cinema market at each year).

Table 5.7 shows the regression results when simulating different marketing strategies: $C_j$+$M_j$ indicates the total budget of movie *j*; $\sigma_j$ indicates the division of the total budget in advertising and production budgets for movie *j* and finally $1-|1/2-m_j|$ indicates the matching between the characteristics of movie *j* and the agents' preferences. As expected, the main driver of the box office is the total budget with which the movie is produced. Movies with low budgets have extremely low chances to become hits of the market. However, the division of the budget and also the matching between agents' preferences and movie characteristics do affect box offices. Movies with low budgets do equally bad at the box office but when movies are produced and advertised with high budgets, both the marketing strategy and the customer satisfaction matter. At any level of competition, the hits of the market are the movies that match agents' preferences and spend in advertisement more than in production costs. Table 5.7 shows the same analysis at higher competition levels. Maintaining the parameters' setting as before, we simulate lower or higher competitions by decreasing or increasing the number of movies released per year. We notice that the total budget remains the most important driver of box office and that the effects of both marketing strategy and customer satisfaction become more relevant, especially the latter. At a higher level of competition, it becomes more important to meet the preferences of the agents and to invest the budget more towards advertising that to production costs.

Table 5.7

Regression analysis. Different levels of competition

| | Low (360 movies) | Normal (480 movies) | High (600 movies) | Very high (720 movies) |
|---|---|---|---|---|
| R Square | .724 | .698 | .689 | .665 |
| Total budget ($M_j$+$C_j$) | .849 (<.001) | .865 (<.001) | .879 (<.001) | .876 (<.001) |
| Division budget ($\sigma_j$) | .340 (<.001) | .320 (<.001) | .349 (<.001) | .341 (<.001) |
| Matching preferences ($1-\|1/2-m_j\|$) | .224(<.001) | .244 (<.001) | .278 (<.001) | .284 (<.001) |

## 5.5 Conclusions, implications and limitations

This chapter, with its proposed simulation model and its analysis, contributes to the literature of entertainment industries in general and of the motion picture industry in particular with three main results. First, the unequal distribution of revenues at the box office is mainly due to the social influence in the decision making of the movie goers. The social influence lets their decisions to converge towards the movies with high advertising budget and high production budget.

Second, our agent based model explains the surprising correlation between the fast decay of the revenues at the cinema theatres and their total box office. Such a correlation is due to the fact that movie goers are more sensitive to the buzz of the movie than to the real quality of the movie. In fact, in our simulation experiments we find that such correlation arises only when the retention of buzz messages is stronger than the retention of quality messages. Big studio producers behave accordingly: they understand that, once an acceptable level of quality is reached, what matters is the buzz that they create around the movie. They strongly advertise their movies before releasing them, they attract as many movie goers as possible at the opening weekend and they do not do much in order to avoid the fast decay after the releases. This result goes against the idea that the best movies are able to build their own legs (De Vany, 2004). This may be true for a few real great movies that, guided by positive WOM, are able to stretch their life cycles for many weeks. Although there exists cases like this (examples are *Titanic*, *Shrek* and *What a Beautiful Mind*), we believe that these are usually rare exceptions. The most common case is that studios prefer to take less risk by producing movies of average qualities and by starting strong advertising campaigns in order to ignite the pre-release buzz. In this way they bring many people at the cinema theatres right when the movie is released, they enter the top classification at the first places and then they decay fast. Stated simply, the higher the buzz produced by the studio producer, the higher the movie enters the box office at the opening weekend, the faster it decays in the following weeks and the higher its total box office at the end of its life cycle.

Third, our agent based model of the cinema market allows us to study the drivers of box office. Due to the restriction at the number of free parameters, that is necessary for a rigorous analysis, we confine the analyzed effects on total budget, division of the budget between advertising and production costs and matching between customers' preferences and movies' characteristics. As expected, we find that box offices are higher when the total budgets are higher, when the movies' characteristics match more movie goers' preferences and when the movies spend more on advertising than on production. This result suggests that in the top classification cases like *Spiderman* and *Lord of the Ring* (big budgets and big revenues) are the most typical ones and cases like *The Blair Witch Project* and *My Big Fat Greek Weeding* (low budgets and high revenues) are extremely rare exceptions. Finally, because our simulation model permits to build different scenarios, we investigate different levels of competition in the market. When the motion picture industry is characterized by an increasing competition, the main driver of box office still remains the total budget of the movies. Moreover, the matching of customers' preferences becomes more important and the division of the budget towards stronger adverting costs maintains its positive effect.

This work is not able to completely exclude any limitation. As any medal has its reverse, we believe that the main limitations of our work are strongly linked to its best aspects. A first example is that our simulation model allows us to rigorously analyze the effects of the variables under investigation (i.e. consumers' preferences, social influence, retention of buzz messages, retention of quality messages, movies' characteristics) but, in order to do so, it has to include different interesting effects like star power, genres, etc. in a unique variable: movie characteristics. This allows us to show the effects of advertising and of production budgets but it forces us to not distinguish different facets of the movie-goer decision making.

A second example is the strict distinction between buzz and wording perceived quality. Our model separates these two streams of messages hypothesizing that they do not affect each other. This artificial separation allows us to show that the correlation between box offices and fast decay of revenues is only possible when the retention of the buzz is stronger than the retention of the wording perceived quality. However, such a separation is obviously somehow artificial. There could be many movies for which the buzz around the movie can be enhanced by the quality of the movie itself and possibly also the reverse can happen.

Besides these limitations we believe that when simulation models like our agent based model are theoretically grounded and when their analysis is rigorous and controllable, they offer high chances to enhance classical marketing studies. They can build detailed scenarios where to test different marketing strategies. In the case of this work, we replicate the USA cinema market with a highly schematic model and we test it with real data. This helps us to show how the demand of real motion picture industry is highly socially susceptible and how in this industry the buzz has become much more important than the real quality of the product.

# 6 Discussion and implications

## 6.1 Theoretical implications

The main goal of this thesis is to incorporate part of the flourishing literature on network structures in a marketing context. Most of the results we have obtained and presented generate several implications. First of all we hope that the reader, after going through these chapters is convinced that often networks do play a role, that they can explain different market dynamics and that studying networks can be used to develop marketing strategies.

Most of the theoretical implications derive from the following metaphor: a new product that diffuses into a society of consumers is like an epidemic that spreads into a population of susceptible individuals. Inspired by this metaphor, we believe that marketing can gain useful insights studying, adjusting and adopting epidemic models. This is what we explicitly do in chapters 2, 3 and 4. We build different network structures of consumers with their preferences and their attributes and we study how the diffusion dynamics of different products vary. Although we believe that the diffusion of a new product might look like the spread of an epidemic, we are also aware that these two processes are not completely the same. A substantial part of the work presented here consists of adapting the epidemic models to a marketing framework that can include product characteristics, personal preferences and social influence.

First, we test different global network structures and we find that new products spread more and faster in scale-free networks compared to regular networks (chapter 2) and in small world networks compared to regular networks and random networks (chapter 3). While the fact that scale-free networks are more efficient than regular networks is an expected result (Pastor-Satorras and Vespignani, 2002), the fact that small world networks are more efficient than random networks is a new and surprising result because it goes in the opposite direction compared to what epidemic models predict. In epidemic models a simple contact may determine the infection of a susceptible individual but in an economic framework the fact that a neighbour has already adopted a new product might be not enough to convince a consumer to adopt the same new product. This is the reason why we find that in networks that are highly clustered (such as small world networks) positive social influence enhances the diffusion and in random networks it does not.

Second, we focus on the effects of local network characteristics studying how the consumers exert influence on the people being part of their personal networks. In chapter 2 we show that social influence may affect the diffusion either negatively or positively. On the one hand, at the beginning of the diffusion process, when the product is just introduced into the population, the fact that a large majority of consumers has not adopted yet represents a strong obstacle for the new product and this can cause a diffusion to fail. On the other hand, if the new product manages to reach a critical mass and to take off, then the social influence inverts its sign and it enhances the diffusion convincing more consumers to adopt. Besides the final penetration of a new product, social influence also affects the uncertainty associated to the diffusion of a new product. Markets characterised by high social influence, where the adoption of the consumers depends more on what other consumers do and less on the individual preferences of the consumers, are very unpredictable. In these cases, the final success or the final failure of a new product may depend on other effects than product characteristics. For example, the seeding of the diffusion plays a relevant role in this kind of markets (see Libai et al. 2005).

Finally we direct our study towards marketing strategies. In chapter 4 we compare two typical promotional seeding strategies for the entry of a new product: the *throwing rocks strategy* and the *throwing gravel strategy*. While the throwing rocks strategy consists of targeting a single group or a few big groups of highly connected consumers as seeds for the innovation, with the aim of igniting the diffusion in a precise area of the network, the throwing gravel strategy consists of targeting little groups randomly as the initial seeds of the innovation and aiming, in this way, at igniting the diffusion in many different areas of the potential market. We find that, especially for markets characterised by high social influence, the optimal strategy in terms of market penetration consists of a balance between the two extreme strategies. The results of our agent based model suggest to ignite the diffusion with groups of cohesive consumers that are large enough to exert strong social influence to others and to place these groups in distant areas of the potential market. This result has proved to be quite robust because it persists within a large variation of different input parameters. However, the simulations generate this result for markets with strong social influence (e.g. brown good durables like DVD players but also clothes, etc.) but it tends to disappear in simulated markets characterized by low social influence (e.g. white good durables like refrigerators but also grocery, etc.). In particular, the lower the social influence consumers experience within a market, the more the optimal strategy moves towards the throwing gravel strategy. This result contributes to show how our agent based model is suitable to test different marketing strategies for different kinds of market.

These first three works of this thesis (chapters 2, 3 and 4) represent a contribution to the field of marketing showing that the combination of micro models about the adoption of the consumers and macro aggregate results about the diffusion of new products is possible and, we believe, useful.

The original design of this thesis expected to study the motion picture market as a typical example of innovation diffusion market. We believed that, as in the classical markets of innovation diffusion, movies could be considered as new products that enter and spread into the market guided first by external influence and then by internal influence. The relatively short life cycle of the movies and the huge availability of data about the revenues at the box office made this market highly attractive for the project. However, the more we dived into the literature of motion picture market, the more we matured the idea that this market is very peculiar and that it highly differs from the classical markets where innovation diffusion is usually tested (e.g. durables). The most evident difference between the motion picture market and the classical innovation diffusion markets consists of a different life cycle of the products. It is very rare to observe movies whose cumulative revenues at the box office resemble the well known S-shaped curve of innovation diffusions (Ainslie et al. 2005; Jedidi et al. 1998; Sawhney and Eliashberg, 1996). For durable goods the sales almost always start at a low level because when these goods are introduced into the market they are initially adopted by a few innovators. This kind of adoption is usually driven by external influence (e.g. mass media advertising). After a certain market penetration has been reached (3-15%) the sales take off and the rest of the potential market, now mainly driven by internal influence (e.g. WOM), adopt (Mahajan et al. 1990b). Movies do not diffuse in this way. Especially for the most visited movies, the slow initial growth does not exist at all. Usually, when a movie arrives at the cinemas, it immediately opens its box office with a very high revenue and then, in the following weeks, its revenues decline rapidly.

Moreover, in markets where innovation diffusion theory is usually tested external and internal influences are often seen as alternative to each other (Mahajan et al. 1990b); usually the WOM, consisting of the advice of a friend, is much more valuable than the mass media message that advertises the new product (Mahajan et al. 1995). Contrarily, in the cinema industry external influence and internal influence heavily overlap and strengthen each other. The strong mass media campaigns that characterize the pre-launch of movies are aimed at creating a buzz around the movie. Here, the suggestion of a friend to another friend for a particular movie is almost always generated by advertisement messages that probably have already reached both; usually this advice is not as valuable as in other markets and it almost always consists of an invitation to go to the cinema together. This characteristic of the cinema market is probably due a particular orientation that today characterizes this industry thoroughly: today cinema means entertainment. A large majority of movie visitors intends the cinema as an entertainment industry and they consume its products as such.

The work presented in chapter 5 corroborates this idea and presents empirical evidence for it. The data about the life cycles of the movies we find a correlation between the final revenues of the movies at the box office and the decay of their revenue during time. Surprisingly enough, the stronger the decay is, the higher the final revenue becomes. We use our agent based model in order to simulate the life cycle of the movies and to compare these life cycles with the real ones. We obtain this relation in the simulated data only when the agents of our model retain advertising messages more or at least equally than quality messages. This means that, given our model, the surprising relation mentioned above is explained by the fact that movie visitors are more susceptible to the buzz around the movie than to the real quality that unfolds after the movie appears into the theatres. Stated simpler, advertisement is more important than quality. This is why the common life cycle of movies consists of high revenue at the opening week followed by a fast decay. Advertisement attracts movie goers at the cinema right after its release. On average, besides the almost inevitable faster decay, the more visitors a movie attracts at the opening weekend, the higher its final revenue becomes.

The fact that the demand of the cinema market is so heavily dominated by the buzzes that the big studio producers and distributors create before releasing their movies creates a very unequal distribution of the shares. In fact, only a few movies succeed in creating strong self-reinforcing buzz and the rest of the movies do not. The work presented in chapter 5 shows how social influences are strong drivers of such observed market inequalities. We show that the strong convergence of the movie visitors' decisions towards the big hits of the market is due to the high influences that these decisions exert on each other. Most of the audience goes to visit big hits such as *Spider Man*, *Harry Potter*, *Pirates of Caribbean*, etc. because other consumers have seen them or because consumers assume that other consumers want to see them. In such a market the production budget and the quality of the product maintain their central role in determining the success of a movie but the powerful impact of buzz that is created around a movie seems to become even more important.

## 6.2 Managerial implications

Nowadays marketing campaigns highly make use of VIPs. Companies pay huge money to VIPs in order to sponsor their performances hoping, in this way, that consumers will associate their brands and their products to the VIPs. Common sense and daily experiences of managers that deal with the launch of new product suggest that the right use of the image of a few VIPs can create a strong visibility for the complete potential market they address. However, surprisingly enough, these campaigns do not immediately guarantee the success of the diffusion. Sometimes they work perfectly (e.g., almost all people that follow tennis remember that Rafael Nadal, the second player of the rankings, wears Nike clothes) and some other times they can remain quite unnoticed (not everybody remembers which brand of clothes Roger Federer, the first player of the ranking, wears).

Models of scale-free networks furnish a simple way to model the structure of markets where VIPs are present. They formalize a network where just a few nodes are connected to almost everyone and the large majority of other nodes has just a few contacts with others. These models can help a marketer to better understand and to direct the processes of the diffusion of a new product that take place among consumers. The fact that in scale-free networks the diffusion spreads more and faster than in other network structures may not surprise an expert marketer. In fact, a marketer knows perfectly that almost all amateurs that play soccer and buy soccer shoes know Ronaldo and that almost all consumers that watch television in the USA know Oprah Winfrey. However, adapting these models to particular marketing contexts including both product and consumers characteristics can result in interesting implications for marketers. For example, do VIPs exert positive social influence to adopt or do they just convey information about the existence of the product? How more (or less) likely is the diffusion to take place when consumers decide more according to their personal preferences than to the behaviours of the others? How more (or less) likely is the diffusion to take place when consumers are more affected by the behaviours of the VIPs compared to the behaviours of their normal friends? What should be the real visibility of the VIPs in order to obtain a significant increment of the market penetration?

In chapter 2 we conduct an analysis on the roles that VIPs play in the networks of consumers. Our simulation results show that, ceteris paribus, VIPs do have a strong positive effect on the final penetration of new products and that their real power consists of the informing role they have in the network. These results suggest that they do not have more convincing power than other normal consumers but their positive effect on the diffusion relies on their high visibility. Once they adopt the new product, almost the complete network knows about it. The implications for the marketers are straightforward: advertising the new product by VIPs seems to be necessary but not sufficient in order to let a new product to take off. If in the target market VIPs exist, it is highly advisable to advertise the new product through them. In fact, these campaigns can guarantee such a high visibility that almost the entire potential market becomes immediately informed about the new product. However, as the practical knowledge of marketers may suggest, these kinds of campaigns do not automatically result in a takeoff of a new product.

In order to deepen our analysis on the determinants of the takeoff of a new product, in chapter 4 we test the timing of promotional strategies. We identify the optimal strategy that determines both a fast takeoff and a high market penetration according to the category of the new product. For white goods (such as laundry machines, refrigerators, etc.), whose markets are not characterized by high levels of social influence, the takeoff usually takes place quite late. Here, marketing campaigns are advised to be placed after at least 10% of the potential market has already adopted. If huge marketing campaigns (e.g. mass media campaign) are placed too soon, they encounter the risk of hampering the final penetration. In fact, if many consumers decide too soon, they may decide not to adopt because not enough other consumers have adopted yet and, in this way, they may ignite a negative social influence. For brown goods (such as TVs, CD players, etc.), whose markets are characterized by high social influence, big marketing campaigns can often anticipate the takeoff of the new product without damaging the final penetration. Here it is advisable to place the campaign very early in the life cycle of the new product, when the market penetration is around 3% of the potential market. In this way, it is possible to anticipate the takeoff and this may result in a competitive advantage compared to other products or brands.

Concerning the cinema market, the practical knowledge of big studio producers and distributors seems to anticipate the implications that the academic studies can offer to them. The advertising campaigns for movies follow almost always the same strategy: *the wide release strategy*. Using this strategy, studios producers try to ignite the buzz around the movie before its release in the cinema theatres by a heavy advertising and by a large number of screens at its opening weekend. Only a minor percentage of the movies, usually low budget movies, uses the *platform release strategy*. This strategy suggests to enter the market with a limited number of screens and then, if the response of the audience is positive, this strategy suggests to drive the positive WOM increasing the coverage of the market with a higher number of screens. But why do big studios prefer so much the former strategy? The cinema market has always been considered a market with very high uncertainty and high risk. It is not easy to foresee the response of the public after the movie enters the cinemas and its real quality discloses to the audience. Studio producers defend their investments by standardizing their productions and their releasing strategies. They try to convince many movie visitors to see the movie at the opening weekend and, in this way, they can rely less on WOM, which is usually too difficult to control and to direct. This has strong implications for the industry: the production of movies focuses always more on the entertainment consumption because this is easier to standardize and consequently the characteristics of the movies become always more similar. Every week there are two or three big budget movies that enter the top-25 classification of the most visited movies at the first places, driven by huge pre-released mass media campaigns. After this high entry, they immediately start their decay in the top-25 classification and, just after a few weeks (8-12 on average), they exit it, leaving space for the next big hits. Consequently, the life cycles of the movies follow the observed fast decay and the chances for other movies (like independent movies) to grow on positive WOM become always more limited.

## 6.3 Methodological Implications

As we mentioned in the introduction of this thesis, all the works presented here heavily rely on the methodology of computational and agent based models. Analytical models for the study of networks are difficult or often impossible to solve and this holds also for network models (Strogatz, 2001). Computer simulations and computational models like agent based models have shown to be highly suitable for the study of networks (e.g. Barrat et al. 2004; Barthélemy et al. 2004; Newman, 2002; Watts and Strogatz, 1998). The practice with all the stages of the agent based modelling (designing, programming and analysis of the results) has allowed us to gain experience and confidence about this methodology and in this section we stress some of its advantages and some of the risks related to its use.

We have taken advantage of many and different features of agent based models. Hereby we confine ourselves to two simple examples: first, the extrapolation of macro variables is generated by the micro specification of the decision making of the agents and it is not difficult to obtain. Here the modeller needs careful design and control of the sequence of the decisions of the agents, a clear and systematic collection of the simulated data that are generated and a click on the start button of the simulation run. Second, the study of uncertain phenomena suits particularly well this methodology. After the design and the implementation of the model, it is possible to conduct many runs with the same simulation settings and the simple standard deviation of the dependent variable is a good indicator of the uncertainty related to the phenomenon under investigation. For instance, in chapter 2 we have done so in order to analyse the uncertainty of the diffusion of the innovation.

However, we have also experienced some risks related to the use of this methodology. The design and the implementation of agent based models can easily become so large and so complex that the results become difficult to interpret. Hence it is important to balance the complexity of the model with the capacity to understand and to explain the simulated data created. One of the most attractive features of agent based models consists of the possibility of including different aspects of the simulated phenomenon and of testing their effects with relatively low effort. Thus, it is highly attractive to include into the design of the study many aspects of the research question. However, we believe that for agent based modellers it is very important not to transform these advantages into an abuse. The analysis of the simulated results has to be rigorous and fully understood both by the modellers and by the rest of the scientific community that may be less familiar with computational models. Often, the sensitivity analysis of the results, that shows how the results vary according to the variations of the input parameters, either does not explain how the simulation model has generated the results or remains incomplete for a vast area of the parameter space. This may represent a strong limitation for this kind of studies because there is no reason to believe that the simulated phenomenon adheres to the description given by the used input parameters. We maintain the idea that a sensitivity analysis of the simulated results can be confined into a particular area of the parameters' space only when there is strong theoretical and/or empirical evidence that the values used as input parameters describe a realistic representation of the explanandum.

## 6.4 Future research

This thesis has investigated the effects of social network structures and social influences on different kinds of markets such as durables and movies. Markets where these effects are relevant are highly complex because these effects are non linear in nature (Arthur, 1994; Arthur et al. 1997). In order to study these effects we have used agent based models because they are highly suitable for analysing these kinds of dynamics (Gilbert and Troitzsch, 1999). However, markets highly differ from each other and not all markets display similar social influences and/or similar social network structures. For example, on the one hand there are markets such as cars, clothes and movies where networks are very dense because these products are very visible and costumers exchange much information about them. On the other hand there are markets such as salt, toilet paper and insurances where networks are somehow less dense because theses products are less visible and consumers talk less about them. We believe that a promising future venue of research for agent based models consists of investigating empirically how the decision making process changes when consumers have to decide about different products (Jager, 2007). For example, Kuenzel and Musters (2007) find that even everyday food products fall into different involvement categories and that different degrees of involvement lead to different kinds of social influence and different uses of personal networks.

Up to now, agent based models are used in many different fields and recently they have been welcome also in marketing studies (Goldenberg et al. 2004; Lusch and Tay, 2004). However, a real empirical foundation of these models is still missing. The micro specification of these models is often inspired by the intuition of the researcher (Epstein, 1999) and, although this does not always represent a limitation, these models would gain a substantial academic value if they could rely on standardized robust calibration procedures for their input parameters guided by empirical data about the decision making of the consumers (Figure 1.1). For example, most of the agent based models make large use of uniform, normal and beta distributions when they simulate heterogeneous populations of agents. However, in the community of agent based modellers there is not a common and standardized methodology that specifies how to link these distributions to the real ones, how to take into consideration the relations, the proportions and the interdependencies among these distributions. Moreover, also the analysis of the outputs of these models may corroborate the relevance of agent based models in the academic world with a more robust test against empirical data. The results of the simulations consist of synthetic data that are often presented as similar to the observed phenomenon under study. We believe that the use of widely accepted models as benchmarks and the use of standard statistical procedures for the analysis of the simulated data may considerably contribute to the reputation of the agent based models in the academic world.

A second venue for future research that would be a natural development for the work of this thesis concerns network models. There are many different ways of formalizing networks. For example, in this thesis we have studied the effects of static and simple network structures that are not empirically tested in the real markets. However, the existing literature on network structures, both belonging to social science and to statistical physics, has continued to increase over the last years. Up to now, it furnishes a huge piece of literature where to find the most adapt models to use in marketing frameworks. Examples of network models that may be suitable for being used and studied in marketing contexts are weighted networks (Barrat et al. 2004) and evolving networks (Kossinets and Watts, 2006). For example, it would be interesting to study how consumers allocate different importance to relatives, to friends and to colleagues (weighted networks) when they are involved in the decisions for different goods; and how consumers select their neighbours in time according to the attributes neighbours display (evolving networks), a process already known in social science as homophily (Davis, 1963).

Finally, a third venue for future research concerns the motion picture market and the entertainment industries in general. It is surprising that the large majority of the literature of the cinema industry focuses on the supply part of the market and just a few works study the demand (Wierenga, 2006). We believe that for entertainment goods the consumers' decision making depends largely on the way consumers are related and on the way they exert influence on each other. Studying their personal preferences towards this kind of goods would be already a significant improvement, especially for the motion picture market. However, this would still be not sufficient for completely depicting the consumers decisions for these entertainment goods. The relevant role that social influences play in these kinds of markets implies that a full analysis of the demand should include accurate studies on the relevance of neighbours' decisions (imitation) and on collective decision making (coordinated consumption).

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# Samenvatting

De hoofddoelstelling van dit proefschrift is om de opkomende literatuur op het gebied van netwerkstructuren in een marketingperspectief te plaatsen. De bevindingen van dit proefschrift zullen in dit hoofdstuk besproken worden. We hopen we dat de lezer, na het bestuderen van deze hoofdstukken, overtuigd is dat netwerken vaak een belangrijke rol spelen, dat de ze verschillende marketingdynamieken kunnen verklaren, en dat het bestuderen ervan nuttig is voor de ontwikkeling van marketingstrategieën.

Het theoretische raamwerk van dit proefschrift is gebaseerd op de volgende metafoor: een nieuw product dat zich verspreidt door een groep consumenten is als een epidemie die zich verspreidt in een populatie van vatbare individuen. Geïnspireerd door deze metafoor verwachten we dat marketing waardevolle inzichten kan verkrijgen door het bestuderen, aannemen en aanpassen van epidemische modellen. We doen dit in hoofdstuk 2, 3 en 4. We ontwikkelen verschillende netwerkstructuren van consumenten met bepaalde preferenties en criteria en bestuderen vervolgens hoe de diffusiedynamiek verschilt per product. Alhoewel, we van mening zijn dat de diffusie van een product veel gelijkenissen vertoond met de verspreiding van een epidemie, zijn we ons bewust dat de twee processen niet exact hetzelfde zijn. Een groot gedeelte van het hier gepresenteerde werk gaat over het aanpassen van epidemische modellen tot een marketing raamwerk dat in staat is om productkenmerken, persoonlijke preferenties en sociale invloed te incorporeren.

Ten eerste testen we verschillende globale netwerkstructuren, en vinden we dat nieuwe producten zich sneller verspreiden in *scale-free* netwerken dan *regular* netwerken (Hoofdstuk 2) en sneller in *small world* netwerken dan *random* netwerken (Hoofdstuk 3). De bevinding dat *scale-free* netwerken efficiënter zijn dan *random* netwerken was in lijn met bestaand onderzoek (Pastor-Satorras and Vespignani, 2002), maar de bevinding dat *small world* netwerken efficiënter zijn dan *random* netwerken is nieuw en verrassend, aangezien deze in tegenspraak is met wat epidemische modellen voorspellen. In epidemische modellen veroorzaakt één simpel contact een infectie bij een vatbaar persoon, maar in een economisch raamwerk is het zo dat als een buurman een nieuw product heeft gekocht, dit nog niet voldoende hoeft te zijn om de consument te overtuigen om hetzelfde product te kopen. Dit is de reden waarom we vinden dat positieve sociale invloed de diffusie versterkt in zeer sterk geclusterde netwerken, zoals de *small world*, netwerken, maar niet in *random* netwerken.

Ten tweede richten we ons op de gevolgen van lokale netwerkkenmerken door het bestuderen hoe consumenten een invloed uitoefenen op mensen uit hun persoonlijke netwerk. In Hoofdstuk 2 laten we zien dat sociale invloed de diffusie zowel positief als negatief kan beïnvloeden. Aan de ene kant, in het begin van het diffusieproces wanneer het product net geïntroduceerd is binnen de populatie, werkt de grote hoeveelheid aan consumenten die het product nog niet hebben gekocht als een obstakel voor de diffusie van het nieuwe product waardoor het diffusieproces tot stilstand kan komen. Aan de andere kant, wanneer het nieuwe product een kritieke massa heeft bereikt, dan heeft de sociale invloed ineens een positief effect op de diffusie van het nieuwe product doordat de grote hoeveelheid van kopers de overgebleven mensen die het product nog niet hebben gekocht weten te overtuigen. Naast het beïnvloeden van de uiteindelijke penetratiegraad bepaalt de sociale invloed ook de onzekerheid geassocieerd met de diffusie van een nieuw product. Markten die worden gekenmerkt door een sterke sociale invloed, waar de adoptie van producten sterk afhangt van andere consumenten in plaats van individuele preferenties, zijn zeer onvoorspelbaar. In deze omstandigheden wordt het uiteindelijke succes van een nieuw product vaak bepaald door andere effecten dan slechts die van de productkenmerken. In deze markten speelt bijvoorbeeld het aspect op welke plaatsen binnen de populatie de adoptie als eerste plaatsvindt een belangrijke rol (zie Libai et al. 2005).

Tenslotte richten we ons op de marketingstrategieën die gevolgd kunnen worden naar aanleiding van de resultaten. In Hoofdstuk 4 vergelijken we twee typen promotiestrategieën die vaak gehanteerd worden bij de introductie van een nieuw product: de *steen-gooi-strategie* en de *grind-gooi-strategie.* De steen-gooi-strategie richt zich op één groep of enkele grote groepen van consumenten die sterk met elkaar verbonden zijn; zij dienen als aanstichters voor de diffusie in een specifiek gedeelte van het netwerk. De grind-gooi-strategie richt zich op het bereiken van veel kleine groepen die als aanstichters dienen voor de diffusie op meerdere plaatsen binnen het netwerk. De resultaten laten zien dat een balans tussen de twee extremen de optimale strategie is om een zo groot mogelijke penetratie te realiseren in markten. Dit geldt vooral voor markten waar de sociale invloed een grote rol speelt. Uit de resultaten van het *agent based model* blijkt dat het verstandig is om de diffusie te stimuleren door grote groepen van hechte consumenten te overtuigen die een sterke sociale invloed kunnen uitoefenen op anderen, en om groepen te benaderen die zich op verschillende plaatsen binnen de potentiële markt bevinden. Deze bevinding blijkt robuust te zijn, aangezien hetzelfde resultaat in veel gevallen gevonden wordt, indien de inputvariabelen veranderd worden. Echter, in de simulaties waarbij de mate van sociale invloed wordt veranderd, blijkt de optimale strategie ook te veranderen. De simulaties met markten die gekenmerkt worden door een sterke sociale invloed (bijv. bruingoed, zoals DVD spelers en kleren) laten zien dat de gebalanceerde strategie optimaal is, maar dit verandert in markten die gekenmerkt worden door een zwakke sociale invloed (bijv. witgoed, zoals koelkasten en boodschappen). Hoe zwakker de sociale invloed is in een markt, hoe meer de optimale strategie verschuift naar een pure grind-gooi-strategie. Deze bevinding laat expliciet zien hoe ons *agent based model* in staat is om verschillende strategieën in verschillende markten te onderscheiden.

De eerste drie onderzoeken van dit proefschrift (Hoofdstuk 2, 3 en 4) dragen bij aan het marketingonderzoek door te laten zien dat het mogelijk en nuttig is om micromodellen die de adoptie door consumenten verklaren te koppelen aan macro geaggregeerde resultaten van de diffusie van nieuwe producten.

Het oorspronkelijke ontwerp van dit proefschrift veronderstelde dat de filmindustrie een typisch voorbeeld is van een markt waar innovatiediffusie vaak plaatsvindt. We waren van mening dat, in navolging van klassieke markten van innovatiediffusie, films gezien konden worden als nieuwe producten die de markt betreden, en dat de verspreiding ervan beïnvloed worden door externe invloeden en vervolgens door interne invloeden. De relatief korte levenscycli van films en de enorme hoeveelheid aan data over de verkopen van tickets in de bioscopen maakten deze markt zeer geschikt voor dit onderzoeksproject. Echter, na bestudering van de literatuur veranderde onze mening en blijkt dat deze markt zeer bijzonder is en sterk afwijkt van de klassieke markten (bijv. duurzame consumptiegoederen) waar onderzoek naar innovatiediffusie gebruikelijk plaatsvindt. Het meest wezenlijke verschil tussen de filmindustrie en de klassieke markten van innovatiediffusie heeft betrekking op de levenscyclus van de producten. Zelden vertoont het verloop van de ticketverkopen van films de bekende S-curve, die gebruikelijk bij innovatiediffusies optreedt (Ainslie et al. 2005; Jedidi et al. 1998; Sawhney and Eliashberg, 1996). Bij nieuwe duurzame consumptiegoederen zijn de initiële verkopen gering, aangezien ze door een beperkt aantal innovators worden gekocht. De adoptie van deze nieuwe producten wordt meestal gestimuleerd via externe invloeden (bijv. via reclames). Nadat een bepaald marktpenetratieniveau is bereikt (3 tot 15 procent), groeit de markt snel en worden potentiële kopers voornamelijk beïnvloed door interne invloeden (bijv. mond-tot-mond reclame) (Mahajan et al. 1990b). Bij films verlopen de verkopen niet op deze manier. Voor succesvolle films bestaat er niet zoiets als langzame initiële groei. Bij deze films is het gebruikelijk dat bij de filmopening de meeste tickets worden verkocht en dus de grootste omzet per week wordt behaald; in de weken neemt de ticketverkoop sterk af. Bovendien maakt de literatuur op het gebied van innovatiediffusie vaak een expliciet onderscheid tussen de timing en de werking van externe en interne invloeden (Mahajan et al. 1990b). Het is bijvoorbeeld gebruikelijk dat consumenten de mond-tot-mond reclame als waardevoller kenmerken en in sterkere mate meenemen in hun beslissing dan de commerciële reclameboodschappen van de aanbieder (Mahajan et al. 1995). Echter de overlap tussen externe en interne invloeden is substantieel en versterken elkaar in de filmindustrie, waardoor het onderscheid tussen de twee effecten moeilijk is te maken. De grootsopgezette mediacampagnes die voorafgaan aan de introductie van de film hebben één doel: het creëren van voldoende *buzz*. Een aanbeveling van één vriend voor een bepaalde film aan een andere vriend komen bijna altijd voor, nadat ze beiden al geconfronteerd zijn met de mediacampagne. In de regel is dit advies minder waardevol dan in andere markten en is het meer een uitnodiging om samen naar de film te gaan. Dit verschijnsel is waarschijnlijk te wijten aan een kenmerk van de huidige filmindustrie: vandaag de dag staat cinema voor entertainment. Het merendeel van de bezoekers ziet cinema als een entertainmentindustrie, en dit bepaalt het consumptiegedrag.

In Hoofdstuk 5 wordt dit idee onderzocht en empirisch bevestigd. Op basis van de data voor de levenscycli voor films vinden we een verband tussen de uiteindelijke ticketverkopen en de sterkte van de daling van de ticketverkopen in de tijd. Verrassend genoeg blijkt dat hoe sterker de daling is, hoe hoger het uiteindelijke bezoekersaantal en de uiteindelijke ticketverkopen zijn. We gebruiken ons *agent based model* om de levenscycli van de films te simuleren en vergelijken dit met de daadwerkelijke levenscycli. Het gevonden verband vinden we alleen wanneer de *agents* in ons model de reclameboodschappen tenminste even lang onthouden als de boodschappen over kwaliteit. Uit ons model blijkt dat het verrassende verband verklaard kan worden via het feit dat bezoekers ontvankelijker zijn voor de *buzz* van een film dan de werkelijke kwaliteit die zich openbaart nadat de film in de bioscopen is verschenen. In meer simpelere bewoordingen betekent dit dat reclame belangrijker is dan de kwaliteit. Dit kan verklaren waarom de huidige levenscycli van films zeer veel bezoekers aantrekken in het openingsweekend, waarna een sterke daling van het aantal bezoekers is waar te nemen in de opvolgende weken. Reclame is in staat om bezoekers te overtuigen om de film te bezoeken direct na de opening. Naast de bijna onvermijdelijke snellere daling van bezoeken, blijkt dat hoe groter de bezoekersaantallen in het openingsweekend, hoe groter de totale cumulatieve bezoekersaantallen zullen zijn.

De vraag naar films wordt grotendeels bepaald door grote filmproducenten en -distributeurs die in staat zijn om voldoende *buzz* te creëren voor hun films; dit zorgt uiteindelijk voor een zeer onevenwichtige verdeling van de marktaandelen. Slechts een beperkt aantal films slaagt erin om een zelfversterkende *buzz* (mond-tot-mond reclame) te creëren. Al samenvattend laat Hoofdstuk 5 zien hoe sociale invloeden een sterk effect kunnen hebben op de waargenomen ongelijkheden in de marktaandelen. Het hoofdstuk toont aan dat de sterke sociale invloeden die bezoekers op elkaar hebben een waarschijnlijke verklaring zijn voor de convergentie van de beslissingen van bezoekers om allen naar dezelfde succesfilms te gaan. De meeste bezoekers gaan naar de grote kassuccessen zoals *Spider-Man, Harry Potter, Pirates of the Caribbean* omdat andere consumenten ze al gezien hebben of omdat andere bezoekers er nog naar toe willen. In zulke markten blijft het productiebudget en de kwaliteit van de film van belang, maar het succes van de film wordt tevens bepaald door de krachtige werking van de *buzz* die ontstaat door het inzetten van grote reclamebudgetten.

Een aantal marketingimplicaties volgt uit de bevindingen van dit proefschrift. Tegenwoordig maken marketingcampagnes veel gebruik van VIP's. Bedrijven betalen enorme sommen geld om hun merken en producten te koppelen aan VIP's om zodoende de prestaties te verbeteren. Gezond verstand en dagelijkse ervaringen van managers die zich bezighouden met de lancering van nieuwe producten duiden erop dat het juiste gebruik van het imago van enkele VIP's voor een zeer sterke zichtbaarheid van het product zorgt voor de doelgroep. Echter, verrassend genoeg, blijken deze campagnes niet altijd garant te staan voor het succes van de diffusie van het product. Enkele zijn ze zeer succesvol (bijv. bijna iedereen die het tennis volgt weet dat Nadal, de nummer twee van de wereld, kleren van Nike draagt), maar het kan ook voorkomen dat ze bijna niet worden opgemerkt (bijv. niet iedereen weet van welk merk kleren Roger Federer, de nummer één van de wereld, draagt).

Modellen van *scale-free* netwerken maken het mogelijk om de structuur van de markt, waarin de VIP's zich bevinden, in kaart te brengen. In een dergelijk netwerk worden VIP's weergegeven door een *node* die met bijna iedereen contact heeft; niet-VIP's hebben daarentegen veel minder contacten. Deze modellen helpen marketeers om de diffusieprocessen beter te begrijpen en te sturen. Het feit dat producten in *scale-free* netwerken zich sneller verspreiden dan in andere netwerkstructuren zal de marketeer niet verbazen. Marketeers zijn zich bewust van dat nagenoeg alle amateurvoetballers Ronaldo kennen, and dat bijna alle Amerikaanse televisiekijkers Oprah Winfrey kennen. Het aanpassen van deze modellen aan marketingcontexten door het incorporeren van productkenmerken en consumenteneigenschappen kan zeer relevante informatie opleveren voor marketeers. Bijvoorbeeld: zorgen VIP's voor een positieve sociale invloed die consumenten overtuigd om het product te kopen of zorgen ze slechts voor een betere naamsbekendheid van het product? Hoe waarschijnlijker of minder waarschijnlijk vindt de diffusie plaats wanneer consumenten in sterkere mate worden beïnvloed door het gedrag van de VIP's en minder door vrienden? Hoe groot moet de zichtbaarheid van de VIP's minimaal zijn om een significante stijging van de marktpenetratie te realiseren?

In Hoofdstuk 2 analyseren we de rol die VIP's spelen in netwerken van consumenten. De resultaten laten zien dat, ceteris paribus, VIP's een sterk positief effect hebben op de uiteindelijke penetratie van nieuwe producten, maar dat de voornaamste kracht in de informerende rol ligt. Deze bevindingen wijzen erop dat VIP's niet meer overtuigingskracht hebben dan 'gewone' consumenten, maar dat het positieve effect op de diffusie te wijten is aan de sterke zichtbaarheid in het netwerk. Als zij eenmaal het nieuwe product kopen, dan weet bijna het gehele netwerk het. De implicaties voor marketeers zijn eenvoudig: reclame maken voor het nieuwe product door VIP's lijkt noodzakelijk, maar niet voldoende om het tot een succes te maken. Als er VIP's bestaan die de doelgroep aanspreken, dan is het zeer raadzaam om het product via hen te promoten. Deze campagnes garanderen een grote zichtbaarheid, zodat bijna iedereen snel bekend wordt met het product. Echter, zoals de praktijk al heeft aangetoond, niet alle VIP campagnes zorgen ervoor dat het nieuwe product een succes wordt.

In Hoofdstuk 4 wordt – met als doel om een preciezere analyse te maken van de determinanten die de verspreiding van het product verklaren – de timing van de promotiestrategieën getest. We veronderstellen dat een optimale strategie ervoor zorgt dat de productverkopen snel groeien en tot een hoge marktpenetratie leiden. Voor witgoed, zoals wasmachines en koelkasten, speelt sociale invloed een minder belangrijke rol en vindt de sterke groei van het product pas laat plaats. Hier is het raadzaam om te wachten met het uitvoeren van marketingcampagnes totdat tenminste 10 procent van de doelgroep het product heeft gekocht. Als bedrijven te vroeg grote marketingcampagnes uitvoeren, dan beperken ze de uiteindelijke penetratiegraad. Wanneer consumenten te vroeg een beslissing nemen – naar aanleiding van de informatie die ze van de leverancier krijgen – dan kunnen ze besluiten om het nieuwe product niet te kopen omdat veel andere consumenten het ook nog niet hebben gedaan. Er is dan sprake van een negatieve sociale invloed. Voor bruingoed, zoals TV's en Cd-spelers, speelt sociale invloed een sterkere rol. Hier zorgen te vroeg uitgevoerde marketingcampagnes er niet voor dat de uiteindelijke penetratie sterk beperkt wordt. Voor deze procten is het raadzaam om de reclamecampagnes vroeg in de productlevenscyclus te plannen, wanneer de penetratiegraad ongeveer 3 procent van de potentiële markt bedraagt. Op deze manier is het mogelijk om te anticiperen op de sterke groei van het product en een eventueel concurrentievoordeel.

De praktische kennis die uit dit wetenschappelijk onderzoek naar voren komt wordt door grote filmproducenten en -distributeurs al in praktijk gebracht. De filmproducenten en -distributeurs hanteren bijna altijd dezelfde strategie: de *wide release strategy*. Deze strategie richt zich op het genereren van zoveel mogelijk *buzz* voordat de film in première gaat door veel reclame te maken en richt zich op het openen in zoveel mogelijk bioscoopzalen. Slechts een klein percentage van de films, waarvan het merendeel met kleine budgetten tot stand is gekomen, gebruikt een *platform strategy*. Hier wordt de film geopend in een beperkt aantal bioscoopzalen, en dan als de reacties van het publiek positief zijn, kan de film meer bezoekers aantrekken en in meer zalen getoond worden door de positieve mond-tot-mond reclame. De vraag rijst waarom de grote filmstudio's de *wide release* strategie verkiezen boven de *platform*strategie? Het antwoord ligt in het feit dat het succes van films moeilijk te voorspellen is. De filmindustrie wordt sinds mensenheugenis gekenmerkt door grote onzekerheid en hoog risico. Het is moeilijk om de reactie van bezoekers te voorspellen nadat de filmpremière is geweest en hoe de kwaliteit zich openbaart aan het publiek. Filmproducenten proberen hun investeringen daarom snel terug te verdienen door hun productie- en openingsstrategie te standaardiseren. Ze proberen zoveel mogelijk consumenten te overtuigen om de film tijdens het openingsweekend te bezoeken. Zodoende worden ze minder afhankelijk van de mond-tot-mondreclame, die lastig te beheersen en te sturen is. Dit heeft zeer sterke gevolgen voor de industrie: de productie van films richt zich meer op het produceren van entertainment films, omdat deze gemakkelijker te beheersen en te standaardiseren zijn. Dit heeft tot gevolg dat films meer op elkaar gaan lijken. Elke week komen er twee of drie *blockbusters* uit die door hun grote marketingcampagnes voorafgaand aan de filmpremière de eerste plaatsen innemen bij de top 25 van de bestbezochte films. Na een week vallen ze direct terug in de lijst van de 25 bestbezochte films, en na een aantal weken (ongeveer 8 tot 12 weken) verdwijnen ze zelfs uit de lijst om ruimte te geven aan andere kaskrakers. Als gevolg hiervan dalen de bezoekersaantallen sterk tijdens de productlevenscycli van de meeste films, waardoor de kansen voor andere films, zoals *independent movies,* om extra bezoekers te trekken via mond-tot-mond reclame kleiner worden.