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Will It Spread or Not? The Effects of Social Influences and Network Topology on Innovation Diffusion

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Innovation diffusion theory suggests that consumers differ concerning the number of contacts they have and 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, a new agent-based model for innovation diffusion is introduced. This model departs 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, it allows consumers to weight the links they have, and it allows links to be directional. In this way this agent-based model tests 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. 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. In addition, results of the simulation experiments show under which conditions highly connected agents (VIPs) determine the final diffusion of the innovation. 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, the simulation results show that when hubs have limits to the maximum number of connections the innovation diffusion is severely hampered, and it becomes much more uncertain. However, it is found that the effect of VIPs on the diffusion curve is often overestimated. In fact when the influence of VIPs on the decision making of the consumers is strengthened compared with the influence of normal friends, the diffusion of the innovation is not substantially facilitated. It can be concluded that the importance of VIPs resides in their capacity to inform many consumers and not in a stronger persuasive power.

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) or through a well-defined network structure (Goldenberg et al., 2009; Watts and Dodds, 2007). This process is addressed as *innovation diffusion* and has been widely studied using field data (for a review, see Mahajan, Muller, and Wind, 2000; Meade and Islam, 2006). From the marketing perspective it is of great importance to understand how information starting from mass media (external influence) and traveling through word of mouth (internal influence) affects the adoption decisions of consumers and consequently the diffusion of a new product.

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Bass (1969) constitutes a fundamental contribution to the field of innovation diffusion by modeling 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; Mahajan, Muller, and Bass, 1990). These models have been used to study the introduction of new products belonging to different categories, from durables (Golder and Tellis, 1997, 2004; Tellis, Stremersch, and Yin, 2003) to entertainment goods like movies (Eliashberg and Sawhney, 1994; Jedidi, Krider, and Weinberg, 1998; Sawhney and Eliashberg, 1996). In this way, a line of research has been initiated that studies whether and how marketing mix strategies affect new product diffusions (Bass, Krishnan, and Jain, 1994; Mahajan et al., 2000; Tellis et al. 2003). Another line of research has focused on the microlevel drivers of adoption by studying how consumer's attitudes and behaviors are affected by product characteristics such as relative advantage, compatibility, complexity, trialability, and observability (Arts, Frambach, and Bijmolt, 2006; Holak, 1988; Holak and Lehmann, 1990; Labay and Kinnear, 1981; Mahajan, Muller, and Srivastava, 1990; Mittal, Kumar, and Tsiros, 1999; Plouffe, Vandebosch, and Hulland, 2001; Rogers, 1995). This stream of research contributed to the present study's understanding of the microlevel factors that determine the adoption by individual consumers.

Despite the two previously mentioned research streams, the effect of microlevel factors on the macrolevel 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 (e.g., cellular automata, agent-based models, percolation models) provide a tool to systematically conduct experiments on how microlevel 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 microlevel and collect the resulting innovation diffusion at the macrolevel. While some percolation models have appeared in marketing science (Gaber et al., 2004; Goldenberg, Libai, and Muller, 2001; Goldenberg et al., 2000; Hohnisch, Pittnauer, and Stauffer, 2006; Libai, Muller, and Peres, 2005; Mort, 1991; Solomon et al., 2000; Weisbuch and Stauffer, 2000), their use is still limited, especially compared with 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 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 that may play a critical role in purchasing a product; for example, in fashion markets consumers exchange not only product information but also norms concerning consumptive behavior (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 microformalization of how individual consumers decide and behave and the aggregation of these decisions at the macrolevel of market penetration (Garcia, 2005). In this way, marketing modelers can study how word-of-mouth and social influences travel in a network of consumers, thus allowing for testing the effects of microcampaigns and marketing strategies on macrolevel innovation diffusion.

The first goal of this paper is to introduce a new agent-based simulation model that integrates

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microlevel behaviors of consumers and macrolevel innovation diffusion. The decision making of the simulated agents is based both on individual preference with respect to product quality and on social influence coming from neighboring agents. The second goal of the present study 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, it is showed 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 reaching the critical mass necessary for the product to take off.

The second market characteristic investigated in this paper is the role hubs have in spreading innovation. A clear example is the Oprah Effect (Peck, 2002). In 1996 the Oprah Winfrey Show resuscitated the publishing industry by launching the campaign, "Get the Country Reading Again." Since the campaign began, the famous Oprah's talk show has generated 38 consecutive best-selling books. In fashionable markets such as sport clothes, 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, Desiraju, and Chintagunta, 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), the results of the present paper show that when hubs have limits to the maximum number of connections the innovation diffusion is severely hampered, and it becomes much more uncertain. The present study's results also show that the strategic position of VIPs in the markets is very important for the diffusion because VIPs make consumers aware of the new product. However, it is found that their effect on consumers' decision making can often be overestimated. In fact, the present study's simulation results show that VIPs do not have a stronger influence on consumers than normal friends do. It can be concluded that the importance of VIPs resides in their capacity to inform many consumers and not in their stronger persuasive power.

The paper is structured as follows. First, a brief presentation is given of what percolation is and how percolation models can be used to formalize diffusions. Then the agent-based model for innovation diffusion is introduced, and the simulation results are presented. Finally, conclusions are addressed, and some managerial implications are discussed.

The Social Percolation Model

In this section, the basic formalization of percolation models (Stauffer, 1994) is presented. The basic structure is a network of agents that usually takes the form of a regular lattice Γ consisting of $L \times L$ cells. Each cell can be in only one of two possible states: not activated (0); and activated (1). Each cell is activated with probability r. Then, the fraction of activated cells will depend on the value of r. Figure 1 shows three possible situations with different r values. A cluster is defined as a group of activated neighbors and neighbors are defined as cells with one side in common. Percolation is defined to occur in Γ when a cluster of cells is big enough to touch at least one cell of each row and each column of Γ. Figure 1 indicates the biggest clusters of activated neighbors. Percolation occurs only in the third case where $r = 0.60$. A percolation threshold r_c is defined as the minimum value of r for which a percolation in Γ is observed.

Solomon et al. (2000) and Weisbuch and Stauffer (2000) use percolation models to formalize hits and flops. In particular, they discuss the diffusion of word of mouth about a new movie that spreads through a population of agents (Eliashberg and Sawhney, 1994; Jedidi et al., 1998; Krider and Weinberg, 1998; Sawhney and Eliashberg, 1996; for a complete review of how the motion picture market contributes to the field

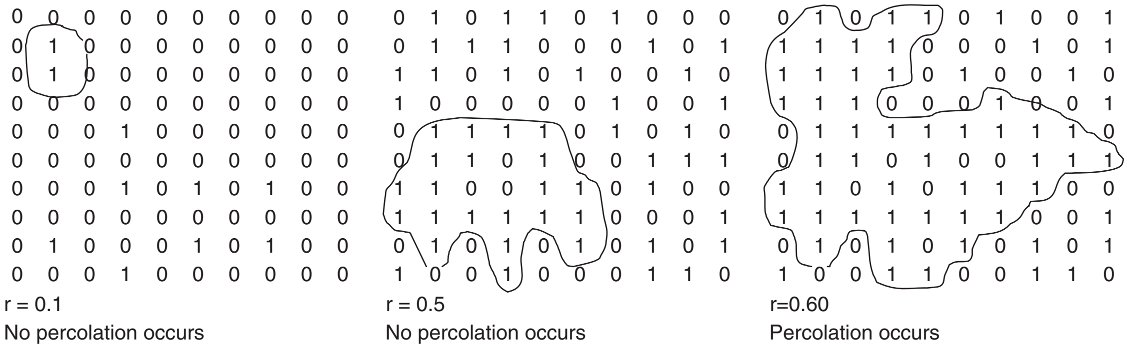

Figure 1: Examples of Percolation Models in a Lattice of 10 × 10 for Different Values of *r*

of innovation diffusion, see also Eliashberg, Elberse, and Leenders, 2006). 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 neighbors about the quality of the movie, q. When an agent, i, is informed about the movie by a neighbor, he or she 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 his or her neighbors 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 does not inform his or her neighbors. 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 who have decided to see the movie are linked in a single cluster. If the cluster of agents who 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 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 who would go 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 go to view 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, Muhamad, and Watts, 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, Jager, and Janssen, 2006; 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 and stimulate the diffusion of epidemics and viruses (Newman, 2002; Newman and Watts, 1999; Pastor-Satorras and Vespignani, 2002; Watts, 2002). Building on this stream of literature, the present study extends 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.).

Agent-Based Model for Innovation Diffusions

In the new agent-based model for innovation diffusions as proposed in this paper, agents decide according to a simple weighted utility of individual preference and social influence. In equation (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}:

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

The importance of the social versus individual utility is weighted by β_i, where β_i can vary between 0 and 1. When β_i is low, agent i is very individualistic, and consequently he or she is hardly influenced by his or her neighbors. On the other hand, when β_i is high, agent i is very socially susceptible, and a large part of his or her utility depends on what the neighbors do. Similarly, the average of β_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

$$x_i = \frac{\sum_j w_{ij}}{\sum_j a_{ij}}. \tag{2}$$

Here, x_i is the fraction of i's neighbors who have 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 who have already adopted). The formulation of the individual utility is captured in equation (3):

$$y_{ig} = \frac{q_g{}^{\gamma}}{q_g{}^{\gamma} + p_i{}^{\gamma}}. \tag{3}$$

Here, p_i is the individual preference of agent i, and q_g is the quality of product g. For large values of γ, if $q_g > p_i$ the individual utility is very close to 1; otherwise, it is very close to 0. It is chosen a value for γ large enough to obtain a bifurcation of the individual utility of the agent. In all simulation experiments presented in this paper it is set as $\gamma = 50$.

Agent i buys product g when he or she 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 equation (4):

$$U_{ig} - U_{min,i} \geq 0. \tag{4}$$

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

A market simulation starts by letting a small percentage of the population δ to adopt the product for free (for all simulation experiments it is set as $\delta = 0.5\%$). Once agent i has adopted, he or she informs the neighbors about the quality of the product. Then, at the next time-steps those informed neighbors compute their utility of consuming the product using equations (1), (2), and (3) and decide whether to adopt according to equation (4). The simulation ends when no more agents adopt. In this model, the following are assumed:

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, δ, is fixed, and the selection of these adopters is exogenous and at random.
4. Choices are binary: Only one product exists, 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 (β_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, he or she decides to buy or not to buy. If he or she buys the product, he or she then informs the neighbors; otherwise, he or she does not. In contrast to percolation models without social influence, in the present model it is possible that an agent first does not adopt when being informed about the product, but later, when several neighbors have adopted, he or she may decide to adopt as well because of the increased social utility of the product. If agent i is informed about product g and he or she decides to adopt it, he or she is considered an adopter until the end of the simulation. If agent i is informed about product g and he or she decides not to adopt, he or she decides at each time-step whether to adopt until he or she decides to adopt or until the simulation ends.

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. The present study examines the effects of different graph structures on the degree of the innovation diffusion. In particular, attention focuses on a particular network structure: the scale-free network.

The shape of a scale-free network is such that many agents have a few neighbors, whereas a few agents have a lot of neighbors. The scale-free network is a network where the probability for each node of having n number of neighbors decays as a power law: $\mathrm{P}(n) \sim n^{-\lambda}$, with $2 \geq \; \geq 3$ (Barabasi and Albert, 1999). This scale-free network is based on preferential attachment (Ijiri and Simon, 1974); that is, 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 neighbors and a large number of agents having just a few neighbors.

Although the scale-free network structure of Barabasi and Albert (1999) permits having heterogeneous agents concerning the number of neighbors, 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 a more realistic version of the scale-free network (Amaral et al., 2000) is adopted. 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 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. 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 100,000

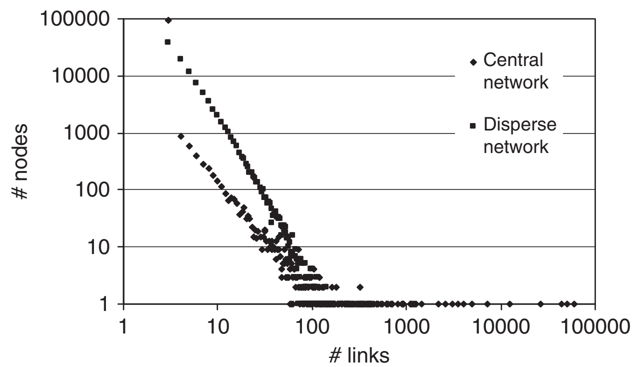

Figure 2: Frequency of Nodes for the Number of Links They Have in Two Social Networks Where the Probability of Each Node of Becoming Inactive Is Varied ($h = 0.01$, disperse network; $h = 0.00001$, central network)

agents, when $h = 0.00001$, the most connected agent (network hub or VIP) has about 60,000 links, and when $h = 0.01$ the most connected agent has about 250 links. The former is called *central network* because most of the agents are connected with a few central agents, and the latter is called *disperse network* because the network is more stretched.

The present study's formalization of social network structures further considers weighted networks. In deciding whether to adopt, consumers may be differentially influenced by those they are connected with (Barrat et al., 2004; Leenders, 2002). In particular, two cases are considered: (1) The influence is equal for all the neighbors; and (2) the influence of each neighbor 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. In equation (1) x_i is modeled such that the social influence an agent obtains from neighbors can vary between these two cases:

$$x_i = c \cdot \frac{\sum_j w_{ij}}{\sum_j a_{ij}} + (1 - c) \cdot \left(\frac{\sum_j \left[\left(\sum_k w_{ij} \cdot a_{jk} \right) - 1 \right]}{\sum_j \left[\left(\sum_k a_{ij} \cdot a_{jk} \right) - 1 \right]} \right). \tag{5}$$

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

In the discussion so far, it is assumed that all network structures have bidirectional links. Here, diffusion patterns in directed networks are also investigated, and this makes the study's 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 other way around. Again, two cases are considered:

(1) The probability of directing the link from i to j is simply 0.5; and (2) the probability of directing the link from i to j depends on the number of links that i and j have—that is, the more (less) links j has compared with i, the more (less) likely that i is directed to j. For the latter specification, it is assumed that among two neighbors it is more likely that the more connected agent attracts the attention of the other. The relinking process takes each link between node i and j and directs it with a probability p as specified in equation (6). The parameter d weights the two extreme cases. When $d = 1$, case (1) is formalized, and when $d = 0$ case (2) is formalized.

$$p(i \rightarrow j) = \frac{\sum_i a_{ji} - d \cdot \left[\frac{1}{2} \cdot \left(\sum_i a_{ji} - \sum_j a_{ij}\right)\right]}{\sum_j a_{ij} + \sum_i a_{ji}}. \quad (6)$$

The last part of the result section describes whether and how weighting and directing the links, as modeled through the parameters c and d, respectively, affect the innovation diffusion.

Simulations: Experiments and Results

Effects of Social Network Structures

To replicate the percolation model of Solomon et al. (2000) with the present study's innovation diffusion model and to test different network structures, agents were allowed to have only individual preferences ($\beta_i = 0$); the minimum utility was drawn for adopting from a uniform distribution ranging from 0 to 1 ($U_{min,i} = [0, 1]$); and the quality of the product was set at 0.5 ($q_g = 0.5$). Finally, individual preferences vary from 0 to 1 on a uniform range of 0.5: for example, $p_i = [0, 0.5]$; $p_i = [0.25, 0.75]$; and $p_i = [0.5, 1.0]$. Moving the average of p ($\overline{p}$) from 0.25 to 0.75, different populations were simulated having low and high individual preferences. The simulation is conducted with only 900 agents because these are enough to replicate percolation models' results and to observe effects of different social network structures. Moreover, for each experimental setting at least 30 runs for each condition are conducted 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 not only are connected locally but also use more remote links (De Bruyn and Lilien, 2004; Dodds et al., 2003). Moreover, some people use more links

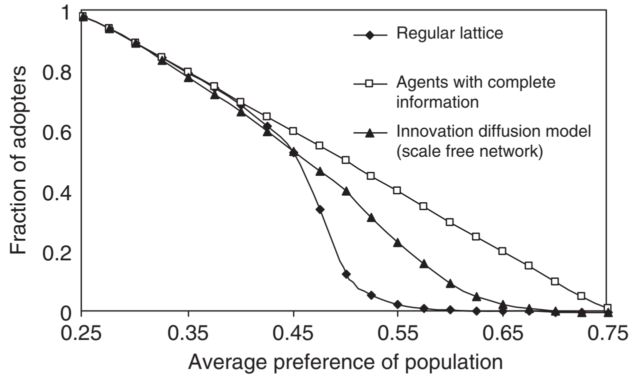

Figure 3: Effects of Network Structures and Average Preference on Final Fraction of Adopters

than others when deciding to adopt a new product. To study how such network assumptions affect the diffusion of innovations, this study tested the effect of different network structures, namely, agents with complete information, agents in a regular lattice, and agents in a scale-free network:

H1: A new product diffuses more in a scale-free network than it does in a regular lattice.

For these simulation runs the average preference of the agents $\overline{p}$ is increased from 0.25 to 0.75 in discrete steps of 0.025, and the average fraction of agents f adopting the product at the end of each run (Figure 3) are computed. Simulation results provide evidence for H1 showing that the structure of the network has strong effects on the diffusion outcome. When agents have complete information, the simulation reproduces the line $f = \overline{U}$ (Figure 3). 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 ($\overline{p} < 0.455$). In this condition information reaches almost all agents, and those agents for whom $U > U_{min}$ adopt the innovation. When $\overline{p} \geq 0.455$, after a certain short time the spreading of information stops, and only a fraction of the agents for whom $U > U_{min}$ adopts. Here, the nonadopting agents do not inform their neighbors, and, as a consequence, information does not reach many agents in the network. Consequently a number of agents who potentially would adopt do not 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 both have complete information about the innovation and do not depend on their neighbors to obtain information on the quality of the new product. In the case of a scale-free network, compared with 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 does the fraction of adopters drop considerably compared with the complete information case. This is caused by the fact that the proportion of agents that do not adopt increases, and hence the likelihood of them getting informed also decreases. 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 ($\overline{p} = 0.5$); still, about 80% of the potential adopters are informed, and half of them adopt. Thus, the scale-free network is much more efficient in spreading information, it approaches the perfect knowledge curve, and it smooths the percolation effect.

High Social Influence versus Low Social Influence

Innovation diffusion theory indicates that consumers vary in the extent to which they experience social influence (Blackwell, Miniard, and Engel, 2001; Granovetter, 1983; Rogers, 1995). Therefore, a new series of experiments is performed testing the effects of varying the average β of the agents ($\overline{\beta}$):

H2: In scale-free networks of consumers, a higher level of social influence leads, on average, to a lower diffusion of the innovation.

H3: In scale-free networks of consumers, a higher level of social influence leads to a higher level of uncertainty about the final penetration of the innovation.

The higher $\overline{\beta}$ is, the more important the behavior of neighbors becomes in the total utility of the innovation. Stated differently, the higher $\overline{\beta}$ gets, the more socially susceptible the simulated market becomes. Experiments for 30 conditions were performed; five values for $\overline{\beta}$ ($\overline{\beta} = \{0.25, 0.375, 0.5, 0.625, 0.75\}$) and six values for $\overline{p}$ ($\overline{p} = \{0.25, 0.35, 0.45, 0.55, 0.65, 0.75\}$) were selected. Simulations were performed with 100,000 agents connected in a scale-free network where agents have at least three links. Simulations ran for 900 time steps, and for all decisions on the other parameters the design of the simulation described in the previous section was adopted. Also in this case at least 30 runs for each condition were conducted to ensure that means and standard deviations of the runs would converge. Figure 4 shows the means and the standard deviations of the runs for the previously specified conditions.

The graph on the left side of Figure 4 indicates that the diffusion of the innovation is hampered by high

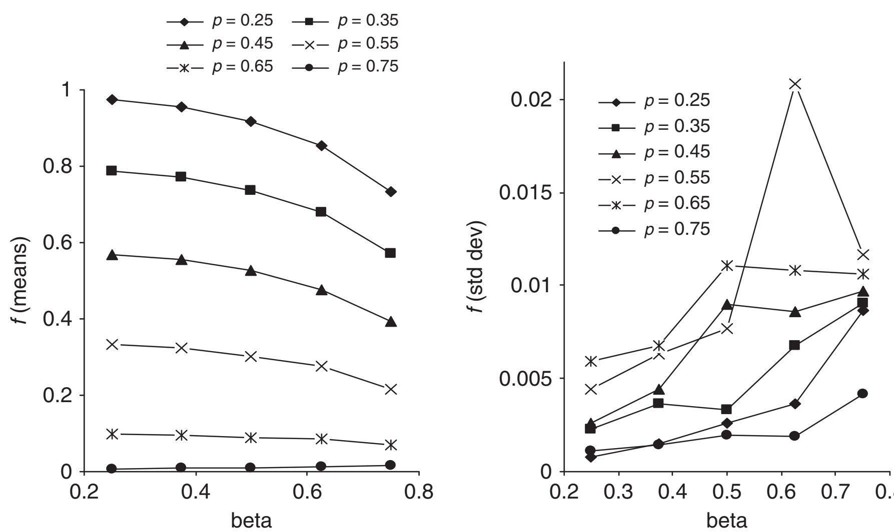

Figure 4: Left Graph: Averages of the Diffusions at the End of the Simulation Runs for Different Levels of Individual Preferences and Social Influences. Right Graph: Standard Deviations of the Diffusions for Different Levels of Individual Preferences and Social Influences

values of $\overline{\beta}$, confirming H2. A high value of $\overline{\beta}$ implies that social influence to adopt is high only if many neighbors 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, Jager, Bijmolt, et al., 2006). 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 with the decrease of adopters observed when social influence drops from $\overline{\beta} = 0.675$ to $\overline{\beta} = 0.75$. Especially when $\overline{p}$ is lower than q_g and when social influence is low ($\overline{\beta} = 0.25$ and $\overline{\beta} = 0.375$), critical mass is reached, social influence helps the spreading of information, and innovation diffuses easily through the population. Agents who do not adopt are just those with very high U_{min}. On the contrary, when social influence is high ($\overline{\beta} = 0.625$ and $\overline{\beta} = 0.75$), critical mass is not reached, and social influence hampers the diffusion. The few agents who 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 4 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 that the success of the product is more difficult to predict. Figure 4 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 4 (right graph) shows also that the uncertainty of the innovation success increases with high values of $\overline{\beta}$, providing support for H3. At the beginning of the diffusion process, highly socially susceptible agents do not consider the individual advantage of the innovation and 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.

Different Markets and Different Networks

As mentioned before, the social utility x_i can be changed to test different hypotheses of social influence. The present paper has already demonstrated that 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 neighbors. Therefore, a cost constraint is attached to each contact an agent has (Amaral et al., 2000). In this way, using two values of the parameter h, two kinds of networks are obtained: central network and disperse network. This paper examines how the innovation diffusion process is affected by these different networks:

H4: In scale-free networks of consumers, a higher level of cost constraints for the number of neighbors of the agents leads to a lower diffusion of the innovation.

H5: In scale-free networks of consumers, a higher level of cost constraints for the number of neighbors of the agents leads to a higher level of uncertainty about the final penetration of the innovation.

Second, while it has been assumed so far that each neighbor 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, 1983). This assumption is relaxed, and the study investigates how diffusion patterns change when the social influence consumers receive from neighbors is weighted according to the number of other neighbors they have:

H6: In scale-free networks of consumers, a higher level of social influence exerted by the more connected agents leads to a higher diffusion of the innovation.

Table 1: ANOVA Model for the Effects of $\overline{\beta}$, $\overline{p}$, 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

Finally, the effects of directed networks are tested. The direction process of the scale-free network is governed by the parameter *d* as specified in equation (6) and changes in the final market penetration of the innovation are collected:

H7: In scale-free networks of consumers, the more the agents direct their links to the VIPs, the higher the diffusion of the innovation.

Centralized Networks versus Disperse Networks. For both central networks and disperse networks, with strong and weak network hubs, respectively, the same experimental design as in the previous section were performed. To assess the effects of individual preference and social influence, an analysis of variance (ANOVA) was performed testing and estimating the effects of $\overline{\beta}$, $\overline{p}$, and *h* on the average degree of the diffusion (Table 1 and Figure 5). 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 before, $\overline{p}$ and $\overline{\beta}$ have negative effects on the penetration of the innovation. Figure 5 shows that *h* also has a negative effect on the market penetration and corroborates H4. The effect of *h* indicates that central networks are much more efficient in spreading the innovation compared with disperse networks. In disperse networks ($h = 0.01$) agents have a strong limit to the number of neighbors, 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 with both $\overline{p}$ and $\overline{\beta}$. The interaction between $\overline{p}$ and *h* is straightforward: When the preferences of the agents are too high, the diffusion will hardly spread in the centralized and disperse networks. More interesting is the interaction between $\overline{\beta}$ and *h*. Figure 5 (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 neighbors, often the hubs of the network. At this point, the social influence a single adopter exerts on a hub is very

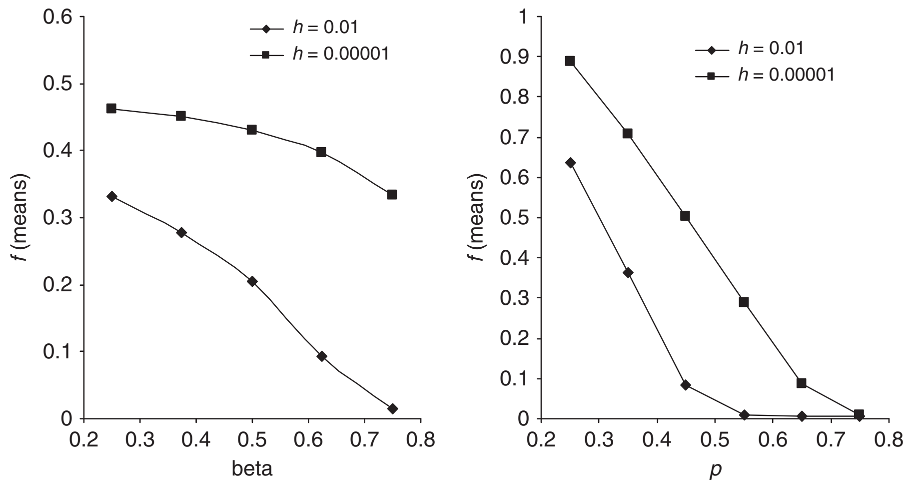

Figure 5: Left Graph: Social Influence Effects on the Average Degree of the Diffusion. Right Graph: The Effects of Individual Preferences on the Average Degree of the Diffusion

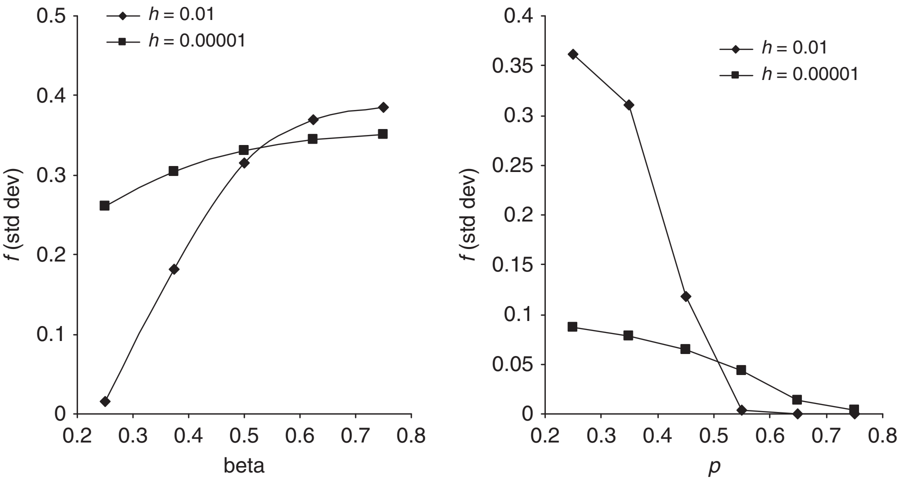

Figure 6: Left Graph: Social Influence Effects on the Standard Deviations of the Diffusions. Right Graph: The Effects of Individual Preferences on the Standard Deviations of the Diffusions

low, because this influence is averaged over the influences of all neighbors, including the nonadopters. This nonadoption effect on hubs becomes stronger when agents are more social susceptible (higher values of $\overline{\beta}$). However, if a hub does happen to adopt, he or she informs many connected agents, thus contributing to the success of the diffusion. In centralized 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 centralized 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 6). This result supports H5. 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 many agents to be informed about the new product, and a successful diffusion can be determined mainly by agents' preferences and product quality.

Weighting the Social Influence of Neighbors. 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, Goldsmith, and Eastman, 1996; Rogers, 1995). The present study investigates how a different specification of the social utility affects the diffusion process. In particular, each contact an agent has is proportionally weighted according to the number of other contacts his or her neighbors have. The parameter c in equation (5) varies from 0 to 1. Simulations for three values of c are performed: $c = \{0.0, 0.5, 1.0\}$, where $c = 1$ corresponds to equal weighting of connections as used in the previous simulation runs. The results are presented in Table 2,

Table 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

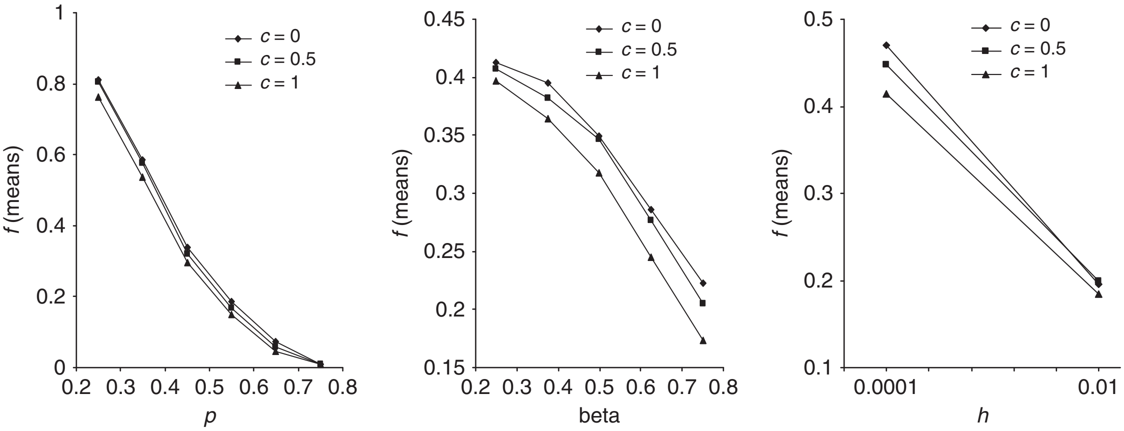

Figure 7: Left Graph: The Interaction Effect of Weighted Networks and Individual Preferences on the Degree of Diffusion of the Innovation. Central Graph: The Interaction Effect of Weighted Networks and Social Influence. Right Graph: The Interaction Effect of Weighted Networks and Network Structures

and the interaction effects between c and the other parameters are shown in Figure 7.

Table 2 and Figure 7 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, the innovation tends to be adopted more easily. However, this effect is very small (partial eta squared is 0.028) when compared with 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, supporting H6, the degree of weighting connections by the number of connections these neighbors have has limited consequences on the final adoption of the product.

Directed Networks of Consumers. For the simulation experiments presented in this section, the same conditions as before are used, but the simulation experiments are performed on directed networks. The parameter d governs the direction of the links. Setting $d = 0$ means that the chances of directing the link from i to j are proportional to the relative number of neighbors i and j have. On the other extreme, when $d = 1$, the chances are purely random. Three values of d ($d = \{0.0, 0.5 \text{ and } 1.0\}$) are investigated. Table 3 and Figure 8 present 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. As predicted by H7, this means that directing the links to the more connecting agents determines a higher market penetration. However, this effect is again very small (partial eta squared is 0.01) compared with the effects of other parameters. The more the network is directed to the more connected agents, the higher the penetration of the innovation. This effect can be explained considering the strength of the social influence. Suppose that i and j are connected and that i has eight neighbors and that j has four. If j is directed to i, i has already adopted, and j has not, then the social influence i has on j is one-fourth. 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 8). In central

Table 3: ANOVA Model for the Effects of $\overline{\beta}$, $\overline{p}$, 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

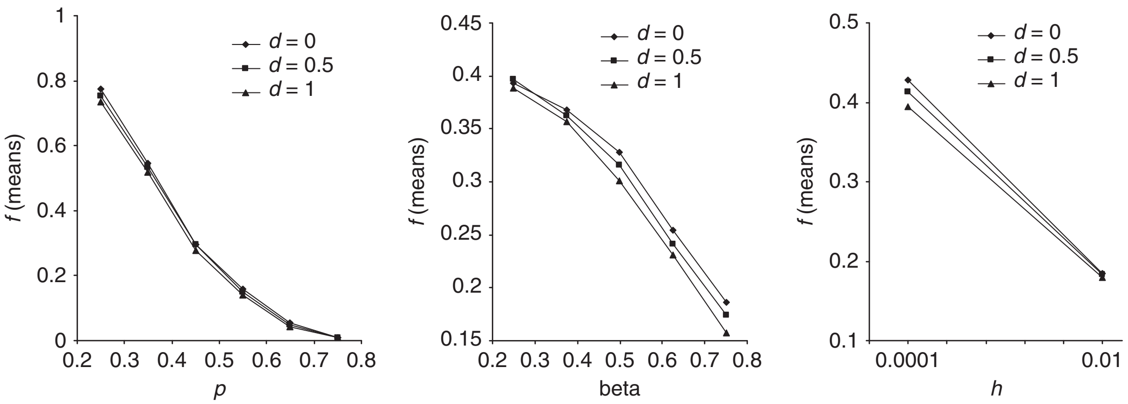

Figure 8: Left Graph: Interaction Effect of Directed Networks and Individual Preferences on the Degree of Diffusion of the Innovation. Central Graph: Interaction Effect of Directed Networks and Social Influence. Right Graph: Interaction Effect of Directed Networks and Network Structure

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), 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 among agents.

Conclusions

This paper proposed a new agent-based model for innovation diffusion. To enhance usefulness to social scientists and marketers for modeling innovation diffusion in a network of consumers, existing agent-based models were modified and extended in several ways. First, the scale-free network structure was adopted, which is less restrictive than traditional structures and has been shown to be efficient in modeling the spreading of viruses and epidemics (Barthélemy et al., 2004, 2005; Newman, 2002; Pastor-Satorras and Vespignani, 2002). Second, the agent decision rules were altered 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, the network structure was modified by (1) constraining the number of connections an agent may have, (2) differentially weighting the connections, and (3) allowing for directed connections. In several simulation experiments, the model and was tested, and the effects of these network features were demonstrated.

The utility a consumer derives from a product is partly a function of the adoption by other consumers in the neighborhood of that consumer (Granovetter, 1983). Such social influences were found to possibly 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 neighbors did not adopt. As a result, the final penetration of the innovation is substantially lower compared with the situation without social influence. Moreover, the uncertainty about the innovation success was found also to increase 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 nonadopters. This study demonstrated that social influences can have either 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.

This first result of this work points toward relevant managerial implications. Because markets with high social influence show a higher level of uncertainty, when facing this type of markets marketers are advised to concentrate their marketing efforts in small periods and in small regions of the potential market. In this way they can obtain a more positive response from the consumers, can overcome the initial negative social influence due to the many nonadopters, and, if a critical mass is reached, can convert the social influence from negative to positive.

The present study also investigated the effects of VIPS (or network hubs) on consumers' individual decision making and on innovations' final market penetration. 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. This study 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 who prescribe the medicine to their patients, but physicians have only a limited number of patients. Here, physicians are more numerous than VIPs and do not have the information power VIPs have. Directing the advertisement to physicians informs only a relatively small number of consumers. This is why, for these kind of markets, direct-to-consumer advertising could be an alternative strategy to stimulate spreading the new product into different areas of the network (Narayanan et al., 2004).

Finally, this study 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, when the weights are stronger for neighbors with more relationships, the innovation was found to reach higher degrees of penetration. However, this effect is relatively small compared with other network factors. A similar result was obtained when the directions of the relationships were considered. The direction of the relationships among consumers was found not to 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; that is, they do not have more social influence than other neighbors. 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 Oprah's Effect, can often be overestimated. The relation VIPs have 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. It is especially hoped that these final results about the effects of VIPs on the diffusion of new products can contribute to the future of the innovation diffusion literature. Although aggregate models can describe and predict many aspects of the diffusion, they tend to consider the market as a whole. Simulating the diffusion of a new product into a network structure where consumers can differently affect each other allows for the study of how single individual decisions can direct a new product toward success or toward failure.

This paper demonstrated how agent-based models can be used to study innovations both at the individual and at the market level. It showed whether and how final market penetration depends on the network features of the market. Such a contribution, inspired by the flourishing literature in statistical physics (Amaral et al., 2000; Hohnisch et al., 2006; Solomon et al. 2000; Stauffer, 1994) aims at importing these methodologies and these tools into the marketing field (see, e.g., Garcia, 2005; Lusch and Tay, 2004).

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 should be used 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 the consumers' preferences are not equally distributed all over the population but instead cluster in different groups? Moreover, many other general questions remain to be answered that may encounter interesting insights using another model but a similar methodology. Critical relevant questions are the following: What happens in the 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.

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