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Will it spread or not? The effects of social influences and network topology on innovation diffusion

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Will it spread or not? The effects of social influences and network topology on innovation diffusion

Abstract

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.

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 addressed as *innovation diffusion* and has been widely studied using field data (for a review, see Mahajan, Muller and Wind, 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 (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, Muller and Bass, 1990a; Tellis, Stremersch and Yin, 2003). 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 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, Frambach, and Bijmolt, 2006; Holak, 1988; Holak and Lehmann, 1990; Labay and Kinnear, 1981; Mahajan, Muller and Srivastava, 1990b; Mittal, Kumar and Tsiros 1999; Plouffe, Vandebosch and Hulland, 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, Goldenberg, Libai and Muller, 2004; Goldenberg, Libai, Solomon, Jan and Stauffer, 2000; Goldenberg, Libai and Eitan 2001; Hohnisch, Pittnauer and Stauffer, 2006; Libai, Muller and Peres, 2005; Mort, 1991; Solomon, Weisbuch, de Arcangelis, Jan and Stauffer, 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, 2001). 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 word-of-mouth 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 paper 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 with respect to product quality and on social influence coming from neighbouring agents. The second goal of our paper 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 Rose, 1990; Bearden and Etzel, 1982) 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, Desiraju and Chintagunta, 2004). Älthough 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, Scala, Barthemely and Stanley, 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 paper is structured as follows: in section 2 we briefly present what percolation is and how percolation models can be used to formalize diffusions; in section 3 we introduce our agent-based model for innovation diffusion; in section 4 we present our simulation results and in section 5 we address the conclusions.

2. The social percolation model

Here we shortly represent 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 Γ 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 I 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 Γ when a cluster of cells is big enough to touch at least one cell of each row and each column of Γ. In Figure I, 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 Γ.

---FIGURE I HERE---

Solomon et al. (2000) and Weisbuch and Stauffer (2000) used percolation models to formalize hits and flops. In particular, they discussed the diffusion of word-of-mouth 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 diffusion ends those 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, 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; Janssen and Jager, 2003; Delre, Jager and Janssen, 2006a; 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).

3. 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}:

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

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 it is hardly influenced by its neighbours. On the other hand, when β_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 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:

$$x_i = \frac{\sum_j w_{ij}}{\sum_j a_{ij}} \qquad (2)$$

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 equation (3):

$$y_{ig} = \frac{q_g{}^{\gamma}}{q_g{}^{\gamma} + p_i{}^{\gamma}} \qquad (3)$$

Here, p_i is the individual preference of agent *i*, 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. We choose a value for γ 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 using the product is higher than its minimum utility requirement. This latter requirement is formalized in equation (4):

$$U_{ig} - U_{min,i} \geq 0 \qquad (4)$$

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 δ 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 equations (1), (2), and (3), and they decide whether to adopt or not according to equation (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 (δ) 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 (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, 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.

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) ~ $n^{-\lambda}$, 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 II 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.

---FIGURE II HERE---

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, Barthélemy, Pastor-Satorras and Vespignani, 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 equation (1) such that the social influence an agent obtains from neighbours can vary between these two cases:

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

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 makes 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 equation (6). The parameter d weights the two extreme cases. When d=1, we have case (a) and when d=0 we have case (b).

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

In section 4.3.2 and section 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.

4. Simulations: experiments and results

4.1 Effects of social network structures

To replicate the percolation model of Solomon et al. (2000) in our innovation diffusion model and to test different network structures, we let agents to have only individual preferences (β_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 a stable value.

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 (Figure III).

Simulation results demonstrate 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 III). However, for the other two structures the fraction of agents adopting the product approaches this upper threshold only when agents' preferences are relatively low. In the 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 $\overline{p}$ ≥ 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 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 the 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 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 III HERE---

4.2. 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 β 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 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 IV shows the means and the standard deviations of the runs for the conditions specified above.

---FIGURE IV HERE---

The graph on the left side of Figure IV 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, Jager, Bijmolt and Janssen, 2006b). 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 IV 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 IV 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 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 IV 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 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.

4.3 Different markets and different networks

As mentioned in section 3.1, the social utility x_i can be changed to test different hypotheses of social influence. In section 4.1 we have showed 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 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 4.3.1 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 4.3.2, 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 4.3.3, 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 equation (6) and we observe changes in the final market penetration of the innovation.

4.3.1. Centralized networks vs 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 4.2. 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 1 and Figure V). 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 4.1 and 4.2, $\overline{p}$ and $\overline{\beta}$ have negative effects on the penetration of the innovation. Figure V 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 to 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 V (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 (non-adopting) neighbours. This non-adoption effect of 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 VI). 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 I HERE---

---FIGURE V HERE---

---FIGURE VI HERE---

4.3.2. 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, Miniard and Engel, 2001; Flynn, Goldsmith and Eastman, 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 with the number of other contacts that neighbour has. The parameter c in equation (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 and the interaction effects between c and the other parameters are shown in Figure VII.

---TABLE II HERE---

---FIGURE VII HERE---

Table 2 and Figure VII 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.

4.3.3. Directed networks of consumers

For the simulation experiments presented in this section, we use the same conditions as in section 4.3.1, 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 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 3 and Figure VIII 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 VIII). 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 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 III HERE---

---FIGURE VIII HERE---

5. Conclusions

In this paper, 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, Barrat, Pastor-Satorras and Vespignani, 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 effect of various 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. 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 many more 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 paper, 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 the consumers preferences are not equally distributed allover the population but they cluster in different groups? Moreover there are 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, Libai and Muller, 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.

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Table I

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

Table II

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

Table III

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

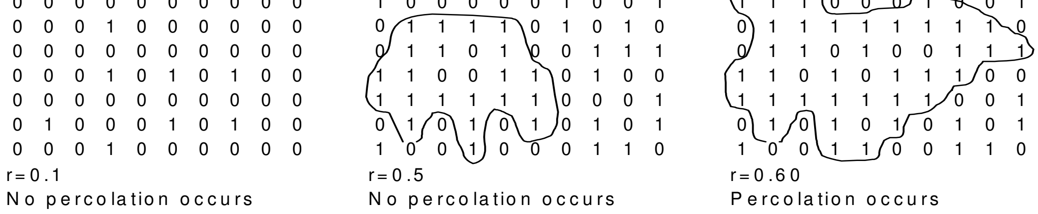

Figure I. Examples of percolation models in a lattice of 10x10 for different values of r.

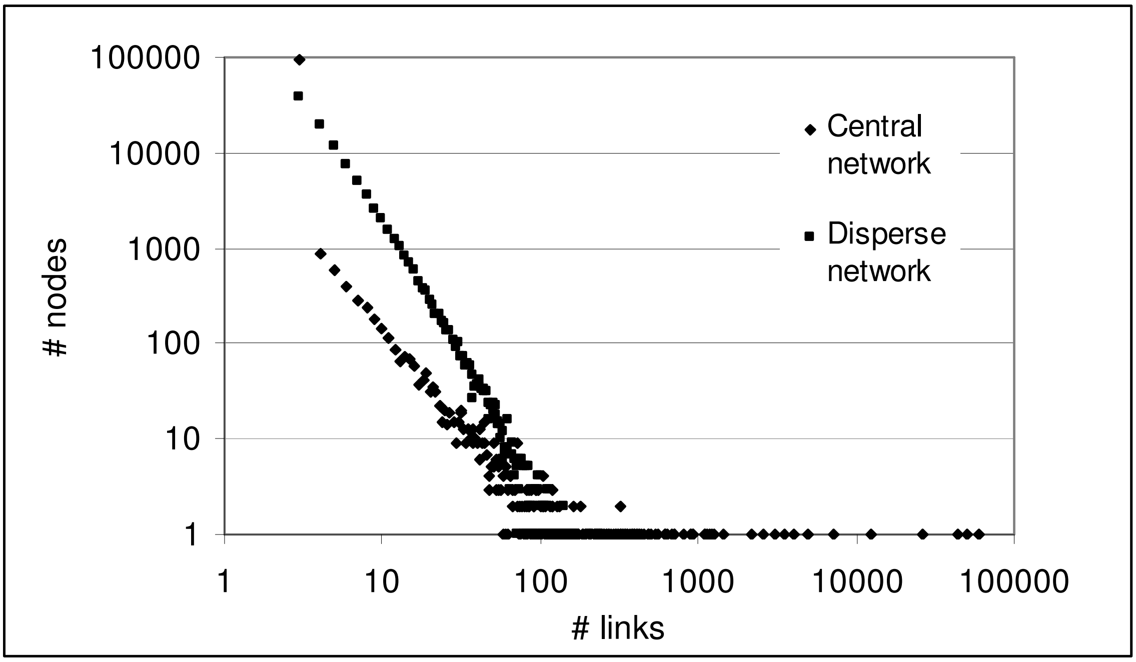

Figure II. Frequency of nodes for the number of links they have in two social networks where the probability of each node of becoming inactive is varied (h=0.01: disperse network and h=0.00001: central network).

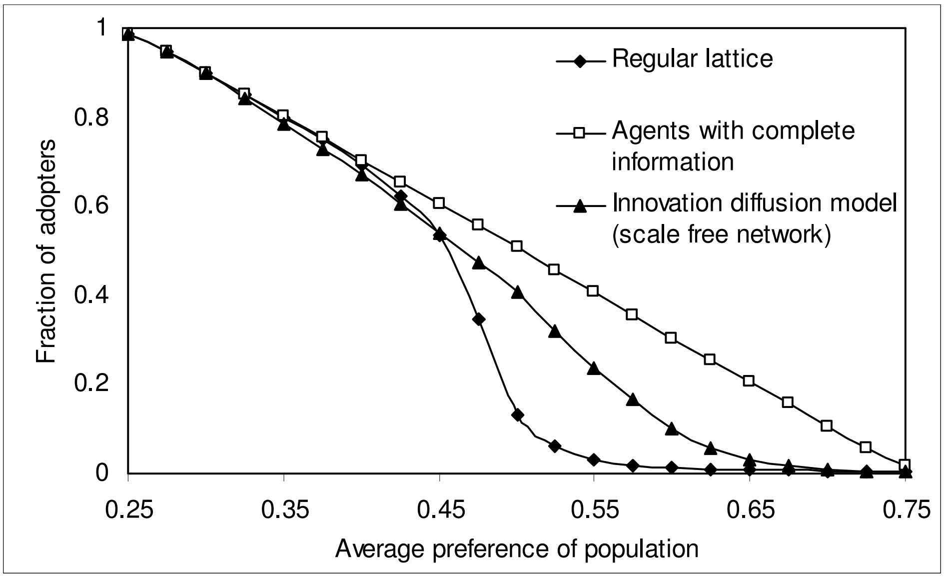

Figure III. Effects of network structures and average preference on final fraction of adopters.

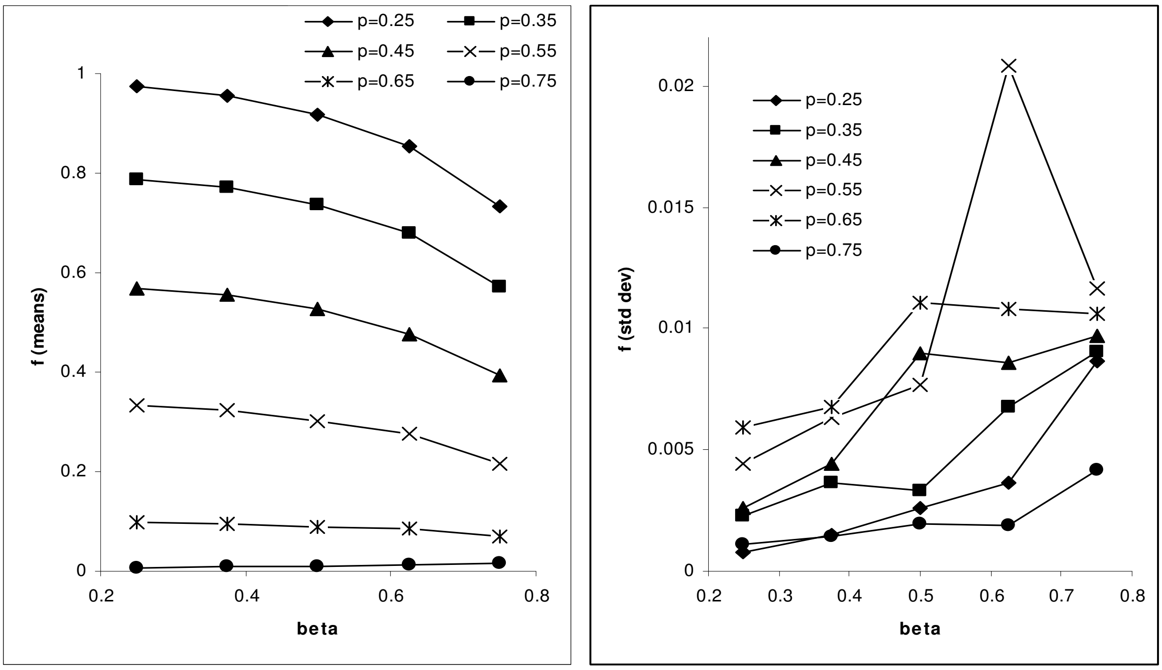

Figure IV. Left graph: Averages of the diffusions at the end of the simulation runs for different levels of individual preferences and social influences; right graph: standard deviations of the diffusions for different levels of individual preferences and social influences.

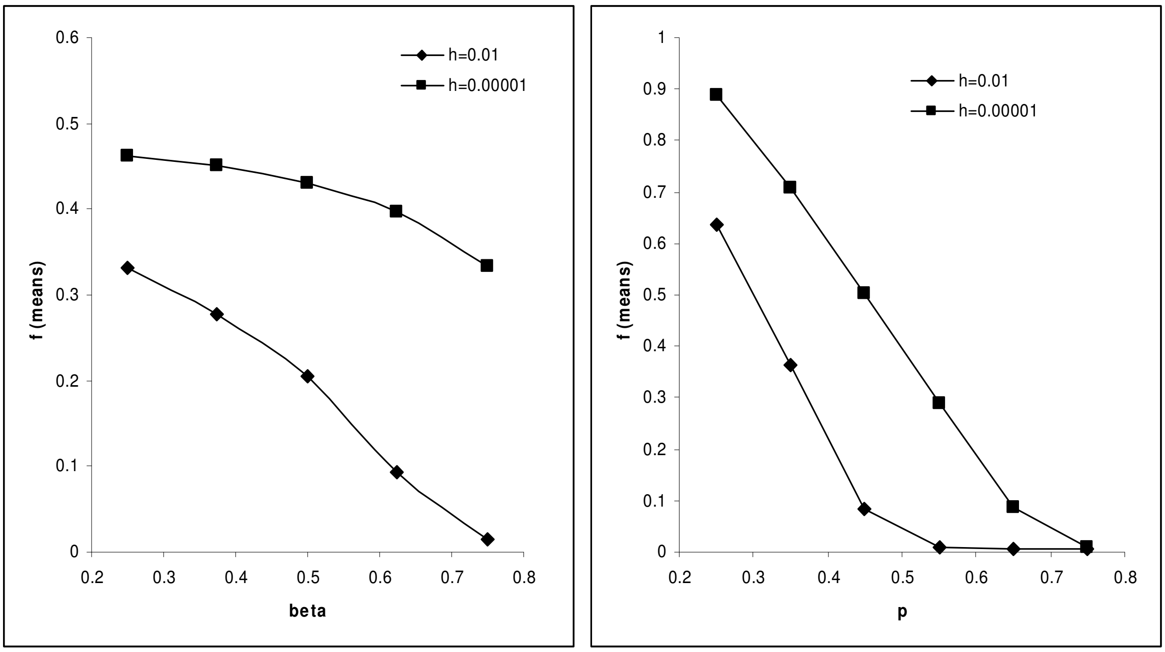

Figure V. Left graph: social influence effects on the average degree of the diffusion; right graph: the effects of individual preferences on the average degree of the diffusion.

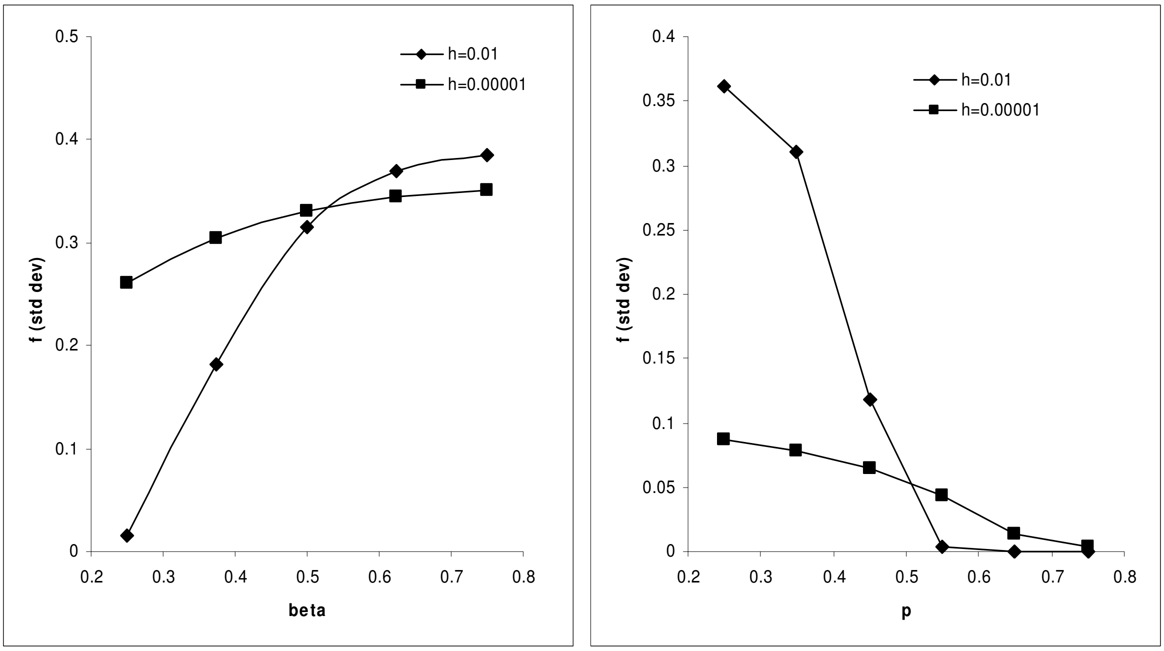

Figure VI. Left graph: social influence effects on the standard deviations of the diffusions; right graph: the effects of individual preferences on the standard deviations of the diffusions.

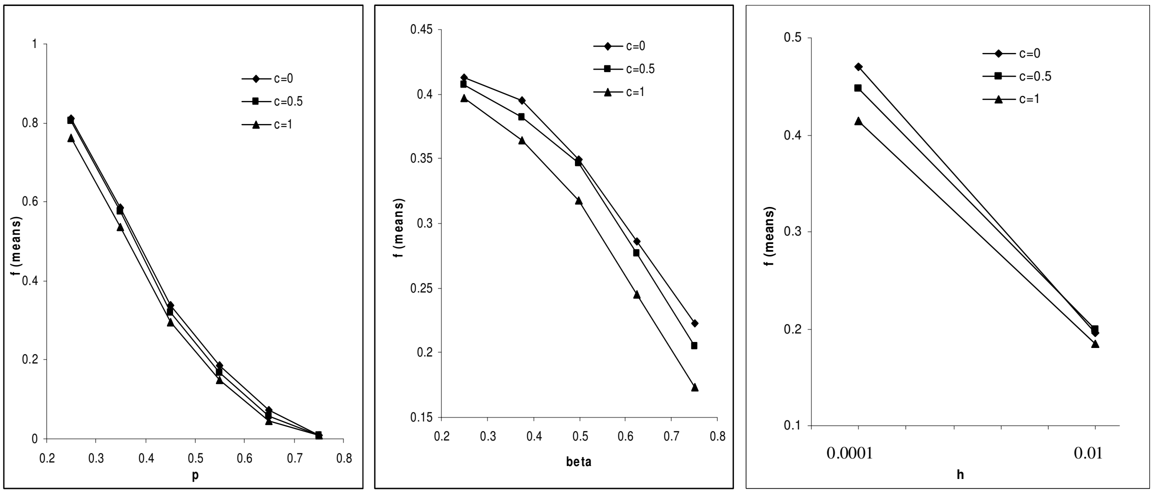

Figure VII. Left graph: the interaction effect of weighted networks and individual preferences on the degree of diffusion of the innovation; central graph: the interaction effect of weighted networks and social influence; right graph: the interaction effect of weighted networks and network structures.

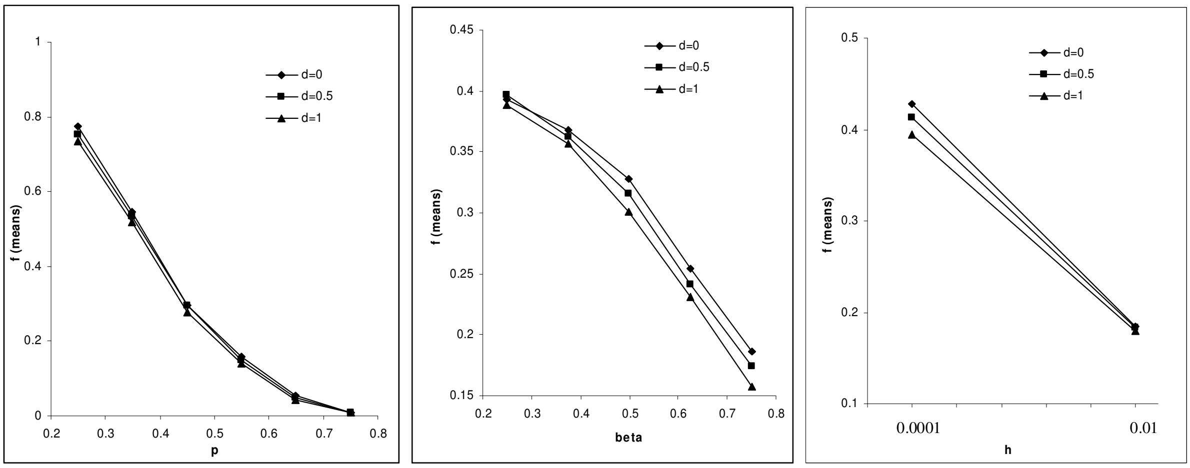

Figure VIII. Left graph: interaction effect of directed networks and individual preferences on the degree of diffusion of the innovation; central graph: interaction effect of directed networks and social influence; right graph: interaction effect of directed networks and network structure.