Simulating Market Dynamics: Interactions between Consumer Psychology and Social Networks

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Abstract   Markets can show different types of dynamics, from quiet markets dominated by one or a few products, to markets with continual penetration of new and reintroduced products. In a previous article we explored the dynamics of markets from a psychological perspective using a multi-agent simulation model. The main results indicated that the behavioral rules dominating the artificial consumer's decision making determine the resulting market dynamics, such as fashions, lock-in, and unstable renewal. Results also show the importance of psychological variables like social networks, preferences, and the need for identity to explain the dynamics of markets. In this article we extend this work in two directions. First, we will focus on a more systematic investigation of the effects of different network structures. The previous article was based on Watts and Strogatz's approach, which describes the small-world and clustering characteristics in networks. More recent research demonstrated that many large networks display a scale-free power-law distribution for node connectivity. In terms of market dynamics this may imply that a small proportion of consumers may have an exceptional influence on the consumptive behavior of others (hubs, or early adapters). We show that market dynamics is a self-organized property depending on the interaction between the agents' decision-making process (heuristics), the product characteristics (degree of satisfaction of unit of consumption, visibility), and the structure of interactions between agents (size of network and hubs in a social network).

1   Introduction

In daily life consumers participate in many different markets. Some markets are stable and are dominated by one or a few products, such as detergents, milk, clothespins, litterbags, and many other household products. In such *locked-in* markets only a few competing products exist, and new products very rarely enter the market. Other markets are very unstable, showing large changes in market share and frequent new product introductions, as in fashion, perfumes, and car models. Here a continual inflow of new products and outflow of old ones can be seen. Prices alone cannot explain the differences in market dynamics. Social processes, such as imitation, conspicuous consumption, and status seeking, appear to play a decisive role in market dynamics such as fads and fashions and more moderate social-susceptible markets. The effects of social processes have for example been acknowledged in stock markets (herding

effects; e.g., [5]) and clothing (e.g., [15]). Hence social processes have to be taken into consideration to explain changing consumption patterns among groups.

Two basic mechanisms are assumed to underlie the social processes that can be witnessed in markets (e.g., [8]). In the first mechanism, the product choice of other people provides a practical heuristic to limit the set of options to choose between. Especially in conditions of uncertainty, people tend to observe the behavior of others to quickly find out about attractive solutions for a decision problem. In particular, the behavior of people similar on a relevant dimension (e.g., income) may provide valuable information. The more people perform a particular behavior, the more frequently it will be observed, resulting in a self-reinforcing process propagating the behavior. Both situational factors (e.g., complex products, unstable markets, visibility of consumption) and personal characteristics (e.g., uncertainty tolerance, motivation to comply) determine the extent to which people are inclined to use this type of social information. Theories and concepts that relate to this type of mechanism are social learning and imitation [2], social comparison [6], and norms [4].

The second mechanism we distinguish is based on social needs that people have. People have needs to belong to a group (belongingness) and express their status and personality (identity) (e.g., [10]). Hence using a certain product may have extra value because a particular group of people is already using it. For example, one may value a large yacht partly because of the status attached to it. Here one may focus on people having higher (financial) abilities as sources of interesting opportunities for consumption. In case of car models, haircuts, and clothing styles such social needs appear to play an important role in the product choice. The approaches of Veblen [17] and successors mainly focus on this second mechanism. Whereas the two mechanisms may operate separately, they often operate combined—for example, a person imitating the clothing style of others to belong to the group. Essential in both types of social processes is the size and shape of the social network through which information is being transferred.

Several scientific disciplines, such as sociology, social psychology, economics, and spatial sciences, have focused on networks as a medium through which empirical phenomena emerge. Especially in the field of sociology there exists a rich tradition in the analysis and formal modeling of social networks. However, whereas large bodies of literature exist on social processes, social networks, and market dynamics, there is up till now no research integrating these literatures. There exists no inventory of the types of social networks that connect consumers in different markets, and how these different types of connections affect the diffusion process or market dynamics. Only one empirical study has been found that investigated the relation between social networks and brand choice [13]. Using graph-theoretic social network techniques, they found that people in more cohesive groups, indicating stronger links between the people, more frequently buy the same brands of products, thus suggesting that a closer social network stimulates homogeneity in consumption. Yet the integration of these literatures is necessary, because market dynamics are often strongly affected by social processes. The shape of social networks through which these social processes commence is hypothesized to be an important determinant of the resulting market dynamics.

A major barrier for integration of these literatures resides in the difficulty of translating micro-level data from case studies to a macro-level market-dynamical context. Newly developed computer simulation techniques allow for this translation, and hence promise synergistic benefits from combining too anecdotal case studies with too abstract computer simulations. In earlier work using a simulation model [9] we explored how different network types affect the dynamics in different types of markets. The social network was formalized as a Watts-Strogatz [18] network, which is represented

as a circle of agents where each agent has contact with some of the neighbours (local contacts) and with a number of random other agents. Using this formalization, we found that if social processes dominate a market, an increase in the size of the network causes the market to be dominated by a few products. However, whereas this work illustrated the importance of social processes and network effects in the context of market dynamics, the results were too abstract to be useful in a practical context. A main objection is that many networks in consumer markets do not conform to the Watts-Strogatz structure. For example, small networks with dense contacts (household, family friends) may exist within a structure with more distant contacts. Moreover, some people have more contacts and influence other people's behavior more than others. Hence our research objectives are (1) to identify the shapes of consumer networks for different product markets, and (2) to explore how these network shapes affect market dynamics.

We hypothesize that people participate in different networks for different markets. The size of these networks may differ as a function of the social needs and/or social heuristics involved in a product choice. For example, whereas you may be well aware of the brand and type of car your friends are driving, the chance that you know which brand of milk they drink or in what type of refrigerator they store that milk is much lower. For different products one may also address different people in one's network. For example, one may talk with some people about cars, and other people about music. Also, some people may have a far larger network than other people, which affects the shape of the network. Again, this may be related to products; for example, a car salesman may have a large number of links related to cars, but only a few related to music. Hence it may be expected that for some products people may have about an equal number of links to other people, and that in other markets some people function as *hubs*, being central in a network and having a disproportional influence on the consumptive behavior of others. Rogers [14] found that especially early adopters are people with a lot of links and a high status in the social network. People in the center of a network may have higher status because of the number of connections, and this status may have a counterpart in how other people value such people's product consumption [16].

2 The Model

Consider a population of N agents where each period the agents make a choice which of the M products to consume. The agents are connected with, on average, k other agents. We call these connected agents *friends*. Products are assumed to differ from each other in a dimension d, which is defined for a range from 0 to 1.

2.1 The Utility of Products

The utility of using a product consists of an individual part and a social effect part. The individual part expresses the difference between personal preferences of a consumer for each product and the product dimension. The preference for product i, p_i, is expressed by a value between 0 and 1. The utility for the product, based on personal preferences alone, is equal to one minus the absolute difference between personal preference p_i and product dimension d_i.

The social effect means that the utility of a product increases when more friends consume the same product. This effect only affects the social need satisfaction. Hence, this effect qualitatively differs from the positive network effect often discussed in connection with markets such as software or faxes, in that here the individual utility is not affected by the number of friends consuming the same product. This social effect relates to the second mechanism as discussed in the introductory setting, and involves

Veblen effects [17] and bandwagons [7]. The variable x_j denotes therefore the fraction of the friends of i who consume product j.

The total expected utility of consuming product j is equal to

$$E[U_{ij}] = \beta_i \cdot (1 - |d_j - p_i|) + (1 - \beta_i) \cdot x_j \tag{1}$$

The components of the utility function—the individual part and the social part—are weighted with β_i and $1 - \beta_i$. A high β_i means that the personal need is weighted more, as is usually the case with more innovative people [12], whereas a low β_i means that the social needs are weighted more, as is usually the case with less innovative people. We do not include prices explicitly in the model. The dimension d_j on which the agents make decisions can include price-related information.

Heterogeneity in the utility function of the agents is thus introduced at two levels. First, it pertains to individual variations considering personal preferences regarding the product characteristics (the value of p_i). Second, it resides in different weights of the personal need against the social need (the value of β_i).

2.2 Cognitive Processing

In deciding what product to consume, the agent may employ different cognitive processes. The type of processing the agent engages in depends on the level of need satisfaction and on the experienced uncertainty.

The need satisfaction of an agent is expressed as $E[U_{ij}]$; it reflects the total expected utility (individual and network) an agent i obtains when consuming product j.

The expected uncertainty $E[Unc_{ij}]$ reflects how uncertain an agent i is about having made the best choice when choosing product j. The more friends in their social network consume other products, the more uncertain an agent is. Furthermore, the value of β_i determines how sensitive an agent is to not having the same choice as his or her friends. The more important the social need (the lower the value of β_i), the more uncertain an agent becomes when his or her friends consume different products:

$$E[Unc_{ij}] = (1 - \beta)(1 - x_j) \tag{2}$$

with $1 - x_j$ the fraction of the friends of agent i who consume a different product than agent i. It is essential that agents start engaging in social processing when their uncertainty exceeds a critical level, which is related to the first mechanism as discussed in the introductory section (imitation, social comparison).

The agents may engage in different cognitive processes in deciding how to behave, depending on their level of need satisfaction (individual and social) and degree of uncertainty. Agents having a low level of need satisfaction and a high degree of uncertainty are assumed to *socially compare*. This implies comparing one's own previous behavior with the previous behavior of agents having similar abilities, and selecting the behavior that yields a maximal level of need satisfaction. When agents have a high level of need satisfaction but also a high level of uncertainty, they will *imitate* the behavior of other sufficiently similar agents. Agents having a low level of need satisfaction and a low degree of uncertainty are assumed to *deliberate*, that is, to determine the consequences of all possible decisions, within a fixed time horizon, in order to maximize the level of need satisfaction. Finally, agents having high need satisfaction and low uncertainty habitually *repeat* their previous behavior.

The threshold parameters $U_{\min}$, the minimum level for satisfaction, and Unc_{T}, the uncertainty tolerance level, are given for each agent. Given the values of U_i and Unc_i,

the type of cognitive processing of the agent can be defined. When a decision is made and the product is consumed, and all other agents have made their decisions and consumed their product of choice, we can calculate the actual utility of consumption U_i and level of uncertainty Unc_i. Note that $E[U_{ij}]$ differs from U_i in that $E[U_{ij}]$ refers to the expected utility of agent i consuming product j, whereas U_i is the experienced utility of consuming product i. The same holds for $E[Unc_{ij}]$ and Unc_i. The following four types of cognitive processes are being formalized:

- *Repetition (satisfied and certain*: $U_i \geq U_{\min}$; $Unc_i \leq Unc_T$). The agent continues to (habitually) consume the product that has been consumed in the previous time step.

- *Deliberation (dissatisfied and certain*: $U_i < U_{\min}$; $Unc_i \leq Unc_T$). The agent will evaluate the expected U_i of each product, and will use a logit function to solve the discrete choice problem in Equation 2. A logit function is a common mathematical model to address discrete choice problems. In discrete choice problems individuals has to make a decision between different options, depending on certain variables. In our case, the options are the different products, and the variable is the expected utility. In the logit function the products acquire a probability Γ_j of being chosen. This probability depends on the relative expected utility. For the expectation we assume that the agents have perfect information on the product characteristics (values of d_i) and use the information on the consumptive behavior of the other agents in the network as observed in the previous period (the observed value of x_i). The products are weighted by the exponent of the parameter b_1 times the expected utility. The higher the value of b_1, the more sensitive is the decision between the products to differences in their expected utility. The resulting probability that agent i chooses product j is Γ_{ij} and is defined as

$$\Gamma_{ij} = \frac{e^{b_1 E[U_{ij}]}}{\sum_j e^{b_1 E[U_{ij}]}} \tag{3}$$

- *Imitation (satisfied and uncertain*: $U_i \geq U_{\min}$; $Unc_i > Unc_T$). The agent evaluates the products that are being consumed by his or her friends. The product with the largest share among the neighbors has a higher probability of being chosen for current consumption. Here too, we use a logit function to describe the discrete choice. But instead of estimating the expected utility, the imitating agent weights the share of other agents consuming product j, with the parameter b_2, which leads to

$$\Gamma_{ij} = \frac{e^{b_2 x_j}}{\sum_j e^{b_2 x_j}} \tag{4}$$

Like the parameter b_1 in Equation 3, the parameter b_2 refers to the sensitivity of the agents in making a decision. Here they are more or less sensitive to differences in the relative consumption of the products by their neighbors.

- *Social comparison (dissatisfied and uncertain*: $U_i < U_{\min}$; $Unc_i > Unc_T$). The agent evaluates the products that are consumed by his or her friends. Using the same logit function as in the case of deliberation, the agent makes a choice between the expected satisfaction resulting from consuming the products that are also consumed by their friends. Thus the socially comparing agent might consider a smaller set of products than a deliberating agent.

2.3 Product Characteristics

The product characteristics are characterized by their potential to satisfy the agents and their visibility. To vary products' ability to satisfy, the utility function of Equation 1 is weighted by a value α reflecting the degree to which a type of product ultimately can satisfy an agent. Consumers are not easily satisfied with products having a low α and spend more time reasoning about their decision in markets characterized by such products:

$$U_{ij} = \alpha \cdot [\beta_i \cdot (1 - |d_j - p_i|) + (1 - \beta_i) \cdot x_j]. \tag{5}$$

The visibility of products is addressed as follows. An agent is linked to a number of other agents, which we call friends. For products of normal (*medium*) visibility the agent will look at this network of friends to determine the social utility. For less visible products the agent will only look at those agents having similar preferences (values of p_i), which we call close friends. Here the agent will use a subset of its network of friends. On the other hand, highly visible products may generate social processes among agents who are not even friends. Here information is also obtained from friends of friends; thus a meta-network is being used that consists of the summed networks of all friends. Thus, assuming products with low, medium, and high visibility, we will use different variations of the social network to simulate information exchange.

3 Social Networks

An important aspect of our analysis of the model is to assess the consequences of different structures of social networks on the choices agents make. During the last few years physicists have developed a number of mathematical models that describe the characteristics of networks found in empirical studies. We will use these different network formulations in our experiments, but first we discuss briefly the different types of networks.

Watts and Strogatz [18] proposed a model for social networks that describes the small-world and clustering characteristics in networks. This model includes empirically found characteristics of social networks, namely the small-world effect [11] and the clustering effect [12]. The small-world effect refers to the experience that despite the large population, the map of who knows whom is such that we are all very closely connected to one another. The clustering characteristic refers to the existence of clusters in social networks. People's circles of acquaintance tend to overlap to a great extent. Your friend's friends are likely also to be your friends.

The model of Watts and Strogatz consist of a regular lattice that has some degree of randomness in it (Figure 1). They construct the network by taking a lattice with periodic boundary conditions, going through each of its links, and with some probability s rewiring that link by moving one of its ends to a new, randomly chosen position. When s is equal to zero, the network is a regular grid; when s is equal to 1, it is a random network.

In recent years large networks, such as the Internet and scientific collaborations, have been analyzed, and a common property of many large networks is that the node connectivities follow a scale-free power-law distribution [3]. It can be hypothesized that such a distribution of connectivities also describes consumer networks. For example, Rogers [14] states that early adopters are typically people having many contacts and a good reputation. Hence they can be understood as hubs in a consumer network. Barabasi and Albert [3] formulated a model that can reproduce these characteristics. The idea is that a network grows over time by adding new nodes. These new nodes have a preference to be connected to other nodes that are already well connected. For
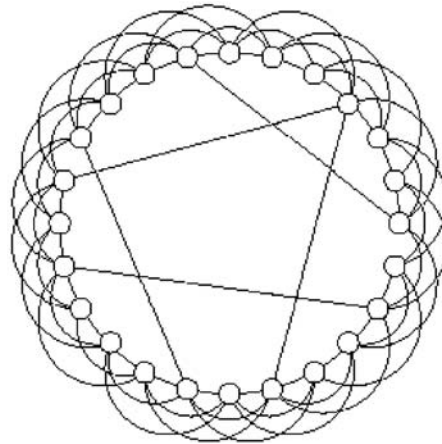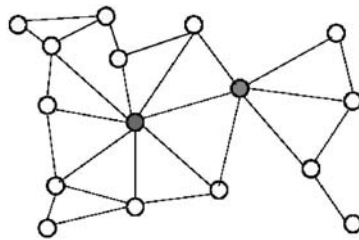
Figure 1. A Watts-Strogatz network.

Figure 2. An example of a scale-free network.

example, if you create a new web page, you are more likely to create links with already well-connected web pages. An example of such a scale-free network is depicted in Figure 2, where it can be seen that most nodes have two or three links, but two nodes have six and eight links, thus having more influence in the network.

Amaral et al. [1] showed that the scale-free network hypothesis is more complex. They analyzed different types of networks and found also networks that followed the power law up to a sharp cutoff. For example, a highly connected node may refuse to accept new connections because of capacity and cost constraints, or a well-connected node may die. Amaral et al. [1] proposed an adjustment of the Barabasi-Albert model by including the option that a node in the network becomes inactive with a certain probability. Since new nodes can only connect with active nodes, they are able to reproduce different classes of observed networks. This approach may be more correct in modeling consumer networks, as consumers functioning as a hub in a network will be limited in the number of contacts they have.

4   Experiments

Consider a market of N (=1000) agents and M (=10) products. The agents have on average 10 friends. The preference for a product p, as well as the value of β, is drawn from a uniform distribution between 0 and 1. The threshold $U_{\min}$ and Unc_T also vary among the population of agents. The values of $U_{\min}$ are drawn from a uniform distribution between zero and one, and the values of Unc_T are drawn from a uniform distribution between zero and one-half. This means that, given an average value of β_i

of 0.5 in the population, the average agent becomes uncertain when more than half of his or her friends consume a different product. Simulations last 100 time steps, and all agents have to make a decision during each time step. The values of b_1 and b_2 are $2/\alpha$ and 4. The factor $2/\alpha$ is used to maintain correct scaling of the skewness for different values of α (Equation 5) in the various experiments.

The performance of agents during the simulations is captured in two aggregated indicators. The first indicator measures *dominance* of products on the market. The higher this indicator, the more the market is dominated by one or a few products. A value of zero means that all products have an equal market share. The dominance indicator is calculated as the average Gini coefficient for the last 10 time steps. The equation for the Gini coefficient g is

$$g = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} |y_i - y_j|}{2M \sum_{i=1}^{M} y_i} \tag{6}$$

where y_i is the number of agents choosing product i.

The other aggregated indicator is the *turbulence*, which is the average change of product choice during the simulation by all agents. Thus turbulence 1.0 means that all agents change their choice each period, and 0.0 means that no agent changes its choice after its initial choice.

4.1 Experimental Design

We performed a series of experiments. First, for a given network we vary the degree of visibility (low, medium, or high) and the satisfaction per unit of consumption ($\alpha = 0.125, 0.25, 0.5, 1, 2, 4, 8$). Furthermore, we test a number of different networks. We denote variations of the small-world network by $SW(s)$, where s is the probability of random links; thus we have a random network for s equal to one, and a regular lattice for s equal to zero. The variations of the scale-free network are denoted by $SF(d)$, where d is the probability of a node becoming inactive when a new node is added. When $d = 0$ the model describes the network of Barabasi & Albert [3]; when $d = 0.01$, that of Amaral et al. [1]. Hence we tested the experimental design shown in Table 1. For each cell in the design five types of networks were tested:

- $SW(s = 0)$—Small world without random contacts.

- $SW(s = 0.1)$—Small world with 10% random contacts.

- $SW(s = 1)$—Small world with 100% random contacts, implying a fully random network.

- $SF(d = 0)$—Scale-free network.

- $SF(d = 0.01)$—Scale-free network with limited links.

Five network formalizations per cell yield a total of $5 \times 21 = 105$ conditions. Running 10 simulations for each condition yields a total of 1050 experimental runs.

4.2 Results

For all the experiments we derive a similar pattern of the distribution of cognitive processes. Figure 3 shows the condition of low visibility of products in a scale-free network $SF(d = 0)$. Product markets typified by products providing a high level of satisfaction (high α) lead to more automatic cognitive processing such as repetition and imitation. When products provide a low level of satisfaction (α is low), the main

Table 1. The experimental design.

Satisfaction per unit consumption (α)

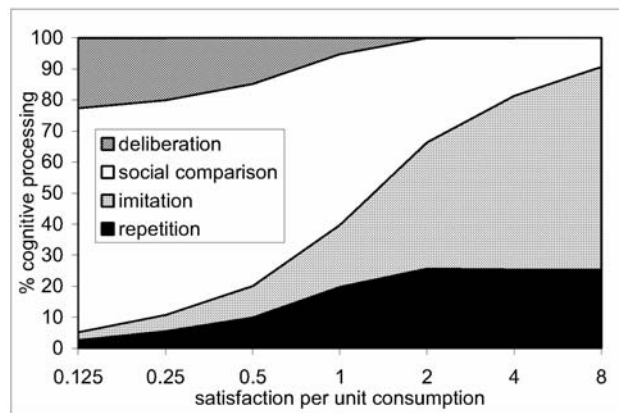| Visibility	0.125	0.25	0.5	1	2	4	8
Low							
Medium							
High							

Figure 3. Share of cognitive processes for different levels of satisfaction per unit consumption (α) for $SF(d=0)$ and low visibility.

cognitive process is social comparison. This explains the turbulence trends as depicted in Figure 4. When the satisfaction per unit of consumption (α) is low, agents are not easily satisfied, performing deliberation and social comparison, and by doing this frequently change their choice. At higher levels of satisfaction per unit of consumption, satisfaction increases and therefore agents more frequently repeat their product choice. An interesting difference between the different levels of visibility is that high visibility leads to lower turbulence. The reason is that agents get information from a larger group of agents, which has a stabilizing effect on the choices made.
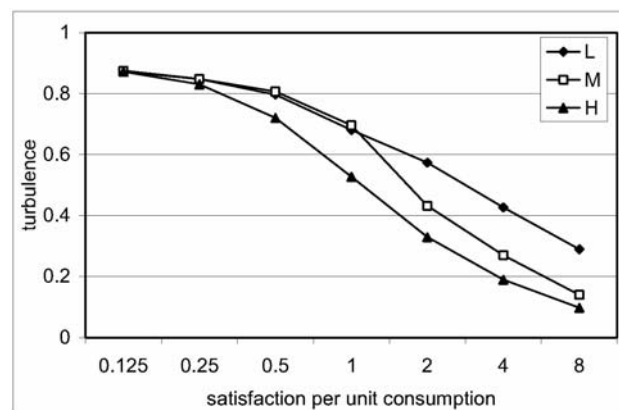

Figure 4. Level of turbulence for different levels of satisfaction per unit consumption for $SF(d=0)$ and high, medium, and low visibility conditions.
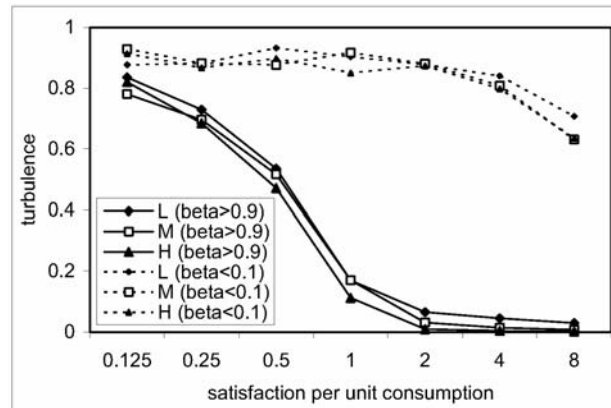
Figure 5. Turbulence for different levels of satisfaction per unit consumption, for agents with a high and a low value of β. The degree of visibility was also varied.

The level of turbulence is not the same for all type of agents. Figure 5 shows the turbulence development for agents that attach a very high weight to their social need (low value of β) and for agents that attach a very high weight to their individual need (high value of β). Agents focusing on their social need remain at a high level of turbulence, even when the level of satisfaction per unit consumption increases. One of the reasons is the higher uncertainty of these agents as defined in Equation 2. Another reason is that the social susceptibility of these agents causes them to change their behavior very easily when friends change their behavior. This may cause cascades of change in the system, yielding in a high turbulence. Agents with a high value of β mainly take into account their personal preferences. When their satisfaction per unit of consumption (α) is low, they may deliberate and try out different products, but when their satisfaction per unit of consumption is higher they will find a product that satisfies them, and they will repeat the choice from then on.

The indicator values of turbulence are very similar for the different types of networks. This is quite different for the indicator values of dominance, as we will discuss below.

In Figure 6 we depict the dominance of products for different conditions. It can be seen that product dominance varies as a function of the satisfaction per unit of consumption, the visibility, and the type of social network.

First, the higher the satisfaction per unit of consumption (higher value of α) leads to a higher level of dominance. The higher satisfaction stimulates more automatic processing, and hence the agents engage more frequently in imitation. This causes them to choose the same product.

Second, higher visibility of the product leads to a higher level of dominance. This is not surprising, since imitators copy the majority choice of a larger population. When one can only imitate from a small number of others, there is a larger chance that small groups emerge consuming the same product (local lock-in). High visibility enlarges the chance that very large groups or all consumers start consuming the same product (total lock-in).

Third, the structure of the social network has an effect on the dominance. A regular lattice in a small world [$SW(s = 0)$] will never have a high degree of dominance, since clusters of similar choices will be local. The structure of the network reduces the spread of information. The higher the probability of random nodes gets, the more social processes will spread a product choice over the population, and hence the more a single product will dominate the market. Figure 7 depicts this relation for high-visibility
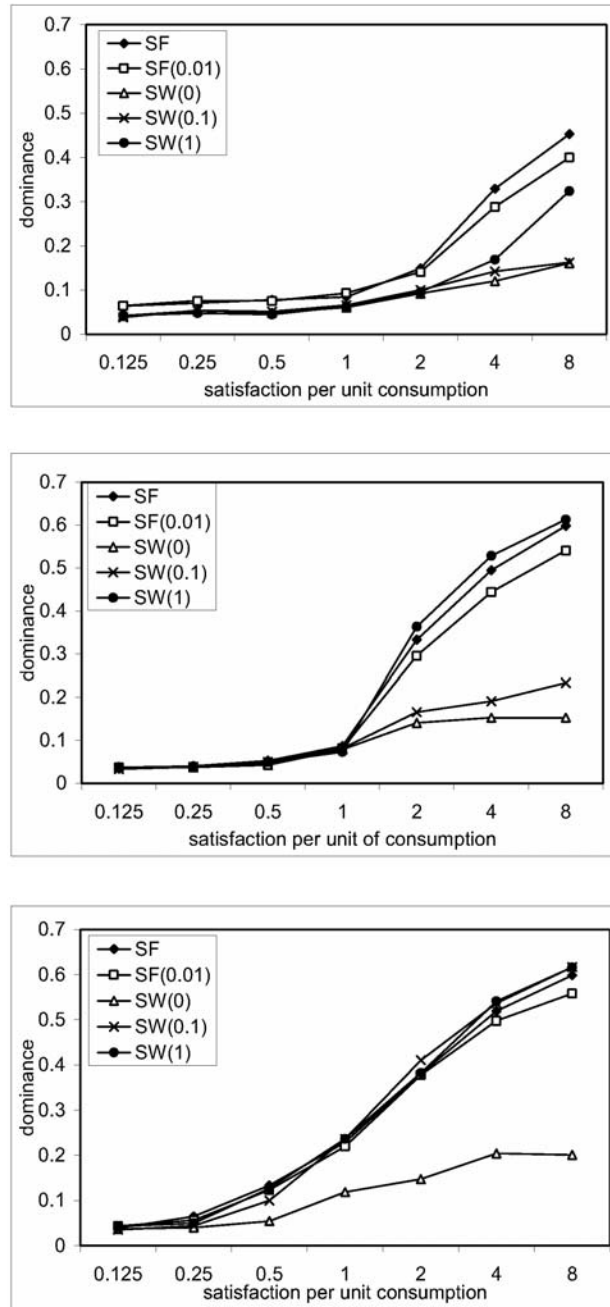
Figure 6. Dominance of different levels of satisfaction per unit consumption, for different types of networks. The top graph represents low visibility, the middle graph medium visibility, and the bottom graph high visibility.
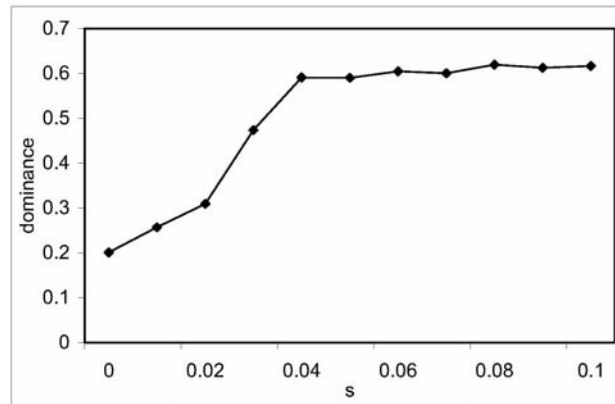
Figure 7. Dominance for different values of s, the probability of random links in a small-world network.

products. Random networks $SW(s = 1)$ even have fairly high values of dominance for low- and medium-visibility products.

However, the level of dominance is in most cases higher for scale-free networks. The hubs cause a fast spread of information, even when the visibility is low. The role of a central node (hub) in a network is very important, because hubs will influence a lot of other agents, and this leads to a more homogeneous choice. Moreover, they may observe very quickly if another agent uses an attractive product. Hence a hub may have easy access to the efforts of many other agents in finding good opportunities for consumption. Of course, people are limited as regards the number of links they can have. However, the simulation results demonstrate that the dominance levels reduce a bit in the limited links condition [$SF(d = 0.01)$], but the results do not differ a lot from the full scale-free condition [$SF(d = 0)$].

5   Discussion and Conclusion

The results presented in this article indicate that besides psychological needs and decision processes, also the size and shape of the network involved in consumer decision making have an important influence on how the market organizes itself. Especially when the satisfaction per unit of consumption is high, as is often the case with products that satisfy lower needs, the results suggest that the shape of the network has serious consequences for the number of products that dominate the market. The results show that a scale-free network yields a market dominated by far fewer products than in the small-world network with a limited number of random links. Even for low-visibility products the hubs have a strong influence on which products other agents consume. Limiting the acceptance of new contacts by these hubs hardly weakens this effect. Hence the simulation results suggest that people with a lot of contacts have a very large effect on other people's consumption. These results are in concordance with Rogers' [14] observation that the early adopters are people with a lot of links and a high status in the social network. Using the network, the hub may be very quickly aware of new, attractive opportunities for consumption, and by adopting them himself he serves as a role model for all the others that are linked to him.

A central question that emerges is how networks affect real-life consumer decisions. It can be assumed that in certain markets the role of a network is virtually absent (for example, when buying milk), but that in other markets people rely heavily on information that is communicated through a network. Here the size and shape of

a network may depend on the type of product involved. For example, when the consumption involves status-relevant products, people may focus on a subset of people in their network who have a higher social status. When the consumption involves the buying of a new computer, one may acquire information from people in the network who have the most experience with computers, independent of their status. And when it concerns the buying of clothing one may compare oneself with others in the network who have about the same opinions as oneself. In some cases the number of other users in the social network may be small, as with computers. On the other hand, one may look at many other people in one's network—for example, to determine what is fashionable.

In empirical research we are planning to identify the shapes of consumer networks for different product markets, and estimate how these network shapes affect market dynamics. The empirical data at the micro level will be used in further refining the simulation model. The experimental outcomes in terms of dynamical processes will be tested against macro-level empirical data from different product markets. Here we want to use time series of product market shares for different brands. The selected product markets will differ on the social importance of products, the types of needs that are involved in these markets (for example, "lower" subsistence needs vs. "higher" social needs) and the degree to which people are satisfied with products.

Acknowledgments

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