Interactions between Market Barriers and Communication Networks in Marketing Systems

Ian N. Durbach
Department of Statistical Sciences
University of Cape Town
Rondebosch 7701, South Africa
ian.durbach@uct.ac.za

Jan H. Hofmeyr
Synovate Brand and Communications Practice
Alphen Business Park
Constantia 7800, South Africa
jn.hofmeyr@iafrica.com

ABSTRACT

We investigate a framework where agents search for satisfying products by using referrals from other agents. Our model of a mechanism for transmitting word-of-mouth and the resulting behavioural effects is based on integrating a module governing the local behaviour of agents with a module governing the structure and function of the underlying network of agents. Local behaviour incorporates a satisficing model of choice, a set of rules governing the interactions between agents, including learning about the trustworthiness of other agents over time, and external constraints on behaviour that may be imposed by market barriers or switching costs. Local behaviour takes place on a network substrate across which agents exchange positive and negative information about products. We use various degree distributions dictating the extent of connectivity, and incorporate both small-world effects and the notion of preferential attachment in our network models. We compare the effectiveness of referral systems over various network structures for easy and hard choice tasks, and evaluate how this effectiveness changes with the imposition of market barriers.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence

General Terms

Performance, Experimentation

Keywords

Social networks, cognitive models, artificial social systems

1. INTRODUCTION

Defection behaviour, that is, why people might stop using a particular product or service, largely depends on the psychological affinity or satisfaction that they feel toward the currently-used product [14] and the availability of more attractive alternatives [17]. However, in many cases the decision about whether to defect or not is also dependent on various external constraints that are placed on switching behaviour, either by the structure of the market, by the suppliers themselves (in the guise of formal or informal contracts), or other so-called 'switching costs' or market barriers [12, 5]. The key feature of all these cases is that the extent to which psychological affinity plays a role in actual decision-making is constrained by market barriers, so that agents are prevented from pursuing those courses of action which would be most satisfying in an unconstrained market.

While the level of satisfaction with a currently-used product will largely be a function of one's own experiences of the product over the period of use, knowledge of any potentially more satisfying alternatives is likely to be gained by augmenting the information gained from personal experiences with information about the experiences of others gathered from casual word-of-mouth communication. Moreover, there is an important relationship between market barriers and word-of-mouth communication. In the presence of market barriers, constrained economic agents trapped in dissatisfying product relationships will tend to disseminate this information to other agents. In the absence of such barriers, agents are free to defect from unsatisfying products and word-of-mouth communication would thus tend to be of the positive variety. Since the imposition of at least some forms of market barriers is often a strategic decision taken by product suppliers, these relationships may be key to the success of a particular supplier.

In addition, the relationship between market barriers and word-of-mouth communication may be a reciprocal one. The structure and function of the network across which word-of-mouth communication is conducted, and particularly the way in which the network changes in response to the imposition of market barriers, also plays a role in determining which market barriers are most effective. These are complex questions, and our main interest in this paper is to address the simpler problems of investigating (a) the extent to which network structure influences the ways in which information is disseminated across a network of decision makers, (b) the extent to which market barriers affect this dissemination, and (c) the consequent implications for overall system performance, in terms of the proportion of agents who are satisfied, and the speed with which the system moves towards equilibrium, which we term stability.

An agent-based model framework allows for an investigation at the level of the individual decision maker, at the

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product-level, or at the level of the entire system; we are particularly interested in the implications of market barriers for the latter two. The model presented here allows for an investigation into the effects of market barriers to be carried out in a complex environment where at every time period each agent in a population must decide which one of a set of products to purchase. These decisions are based on multi-attribute information gathered by personal product trials as well as from the referrals of agents. Agents use this gathered information to search for a product that exceeds their satisfaction thresholds on all attributes – so that the agents may be said to be satisficing rather than optimising (e.g. [15]). Market barriers may act to influence an agent to continue to use a product that is no longer offering satisfactory performance. We allow agents to hold different opinions about the performance of a product, so that as a result a referral from another agent may not lead to a satisfying experience. Agents therefore adjust their evaluations of the validity of other agents' referrals according to the success of past referrals, and use these evaluations to judge whether or not to make use of any further referrals. The level of satisfaction provided to an agent by a product is itself inherently dynamic, being subject to random fluctuations in product performance as well as a tendency for an agent to discount the performance of a product they have used for a long time – a process akin to habituation.

2. BACKGROUND

2.1 Word-of-mouth communication

Much of the work done on word-of-mouth communication in the context of social psychology and marketing research has focused on its forms and determinants, suggesting that word-of-mouth arises in three possible ways: it may be induced by a particular transaction or product experience [11], particularly when that transaction has been an especially good or bad one [1]; it may be solicited from others [10], usually when the task involved is difficult, ambiguous, or new [7]; and it may come about when talk of products and brands arise in the course of informal conversation, particularly when a 'passion for the subject' is present [4]. Word-of-mouth becomes more influential when the source of the communication is credible, with credibility decisions based largely on one or a combination of evaluations of professional qualification, informal training, social distance [7], and similarity of views and experiences [3].

The role of word-of-mouth communication on the behaviour of complex systems has been studied in both analytical and simulation models. The analytical work in [8] investigates the conditions under which word-of-mouth leads to conformity in behaviour and the adoption of socially efficient outcomes (e.g. choosing an alternative that is on average better than another), finding that conformity of behaviour arises when agents are exposed to word-of-mouth communication from only a small number of other agents, but that this conformity may result in socially inefficient outcomes where the tendency toward conformity is so strong that it overwhelms the influence of the superior payoffs provided by the socially efficient outcome. Simulation-based investigations of word-of-mouth [6, 13] have focused on developing strategies for ensuring that a system reaches an equilibrium level where all agents are satisfied, largely by learning about the effectiveness of others' referrals or by varying the degree of inertia in individual behaviour. These studies have found that, given a sufficient number of service providers, honest referrals lead to faster convergence to satisfactory distributions than deceitful ones, and that both forms of word-of-mouth provide better performance than none at all. The simulation framework allows for a more complex modelling of the environment than the analytical models, in which referrals are at random and only two choices are available, and the work in [6] in particular is a close antecedent of the work presented in this paper, our main contribution being to include network structure and the constraints imposed by market barriers as additional effects.

2.2 Market barriers

The extent to which market barriers are influential in affecting systems behaviour draws attention mostly from economists interested in how barriers distort competition and marketers interested in how barriers distort consumer choices. While the formalisation of the idea that satisfaction drives purchase behaviour can be traced back to the work of Fishbein and Ajzen [9] on reasoned choice, nearly all writers, including Fishbein and Ajzen, recognise that this relationship can be thwarted by circumstances (e.g. [17]).

A useful typology of market barriers distinguishes 'transactional' barriers associated with the monetary cost of changing (e.g. in financial services), 'learning' barriers associated with deciding to replace well-known existing products, and 'contractual' barriers imposing legal constraints for the term of the contract [12]. A different typology [5] introduces the additional aspect of 'relational' barriers arising from personal relationships that may be interwoven with the use of a particular product.

There is generally little empirical evidence on the relationship between the creation of barriers to switching and the retention of a customer base, and to the best of our knowledge no previous work using agent-based modelling to generate empirical findings. Burnham et al. [5] find that perceived market barriers account for nearly twice the variance in intention to stay with a product than that explained by satisfaction with the product (30% and 16% respectively), and that so-called relational barriers are considerably more influential than either transactional or learning barriers. Further, they find that switching costs are perceived by consumers to exist even in markets which are fluid and where barriers would seem to be weak. Simply put, market barriers appear to play a greater role in what people do than satisfaction; and their presence may be more pervasive than is generally thought.

3. MODEL FRAMEWORK

3.1 Product performance evaluations

We use a problem representation in which, at each time period, every agent must decide which one of a set of products to choose. Let $A = \{a_k\}_{k=1\ldots p}$ be the set of agents, $B = \{b_i\}_{i=1\ldots n}$ be the set of products, and $C = \{c_j\}_{j=1\ldots m}$ be the set of attributes on which the choice decision is to be based i.e. the decision to be made is a multiattribute choice one. Let $f_j : B \to [0, 1]$ be an increasing function providing the intrinsic performance of a product on attribute j (so that 0 and 1 are the worst- and best-possible performances respectively), and $S_{ij} : A \times [0, 1] \to [0, 1]$ be a subjective opinion function of agents. The intrinsic performance of product i on attribute j is given by $f_j(b_i)$. However, the subjective opinion of the level of performance (of product i on attribute j) given by agent k is given by $s_{ij}(a_k, f_j(b_i))$. All subsequent modelling is based on these subjective performance ratings. For the purposes of this paper, each agent belongs to one of three equally-sized groups, with each group possessing its own subjective performance ratings.

We assume that the subjective performance ratings are not known *a priori* by the agents, and it is their task to discover these ratings by a combination of personal exploration and referral gathering. In order to model this process we introduce the notion of *perceived* performance ratings at time t, denoted by $p_{ij}(a_k, f_j(b_i), t)$. Initially, all perceived performance ratings are set to zero, so that the initial selection of a product is done randomly. Subsequent variation in product performance over time is modelled using two quantities: a random perturbation ϵ_{jkt} applied at each purchase occasion ensures that the experience of a particular product can vary over purchase occasions for the same agent, and a habituation discounting factor H_{ikt} tends to decrease the perceived performance of a product over time as boredom creeps in with repeated usage. Our habituation mechanism supposes that habituation builds up with repeated use of a product, and is used to discount the performance of the product. In most cases i.e. unless the habituation factor is one or extremely close to one, this habituation-based discounting eventually leads to defection, after which the level of habituation dissipates as time passes without the product being used. More formally, once a product i^* has been chosen by agent k, the subjective level of performance is perceived and $p_{i^*j}(a_k, f_j(b_i^*), t)$ is set equal to $s_{i^*j}(a_k, f_j(b_i^*))H_{i^*kt} + \epsilon_{jkt}$, where ϵ_{jkt} is distributed as $N(0, \sigma)$ and H_{i^*kt} is an decreasing function of the number of time periods that agent k has been exposed to i^*.

In evaluating the performance of a product, agents make use of a satisficing framework by comparing the perceived performance of the chosen product with their satisfaction thresholds $\Gamma_k = \{g_{1k}, \ldots, g_{mk}\}$, with $0 \le g_{ik} \le 1$. Agent k will be satisfied with a product i^* selected in time t if $p_{i^*j}(a_k, f_j(b_i^*), t) \ge g_{jk},\ \forall j$.

3.2 Decision processes

In designing the mechanism by which agents make their choice decisions, we allow for the possibility that satisfied agents defect from the products that are currently satisfying them. Satisfied agents stay with their current product with probability $\Pr(stay)$, with a strategy prohibiting satisfied agents from moving (e.g. [6]) obtained as a special case when $\Pr(stay) = 1$.

A defecting satisfied agent decides on which product to choose by considering all other products for which it has information, either by previous personal exploration or by referrals from other agents. The selection of a new product begins by the agent identifying those products from which he or she expects to gain a satisfactory performance on all attributes i.e. those products for which $\delta_{ik} < 0$, where $\delta_{ik} = \max_j[g_{jk} - p_{ij}(a_k, f_j(b_i), t)]$, and selecting a product from this set with selection probabilities proportional to $-\delta_{ik}$. If no satisfactory product exists (or at least the agent is unaware of any such product) the agent identifies those products that offer at least a minimum level of 'acceptable' performance γ_k^-. The minimum level of acceptability is defined as the maximum deviation from his or her aspirations across all attributes that the agent is willing to accept i.e. a product is minimally acceptable if and only if $\delta_{ik} < \gamma_k^-$. Agents then select a product at random from the set of minimally acceptable products. If the set of minimally acceptable products is empty, agents select a product from the full set of products B at random.

The decision process followed by unsatisfied agents is largely similar to that of defecting satisfied agents, with the exception that at the outset of the decision process agents will chose to explore a new product, chosen at random from the set of remaining products, with probability α. With probability $1 - \alpha$, they will use a decision process like the one outlined above for satisfied agents.

3.3 Constraints on decision processes

In some circumstances market barriers may exist that make switching between products more difficult, particularly where some switching costs are incurred as a result of changing one's choice of product. When barriers are present, agents do not switch when they become unsatisfied, but rather only when the performance evaluation drops below some critical level i.e. when $\delta_{ik} > \beta$, where $\beta > 0$ measures the strength of the market barriers. Although in this paper market barriers do not vary over products or time, it is straightforward to allow this to occur by allowing barriers take the general form $\beta = \max(\beta_* + \Delta t_{use}, \beta^*)$, where β_* is a barrier to defection that is applied when the product is purchased for the first time (e.g. a contractual agreement), Δ is the increase in barriers that are incurred for every additional time period the product is used for, and β^* is the maximum possible barrier, and all three quantities are allowed to vary over products i.e. be a function of i.

3.4 Referral processes

Each agent is assumed to be connected to $q_k < p$ agents i.e. to give and receive information from q_k other agents. The network over which word-of-mouth communication travels is governed by the small-world effect [18], by which networks simultaneously exhibit a high degree of clustering of agents into 'communities' and a short average path length between any two agents in the network, and preferential attachment [2], by which agents with greater numbers of existing connections are more likely to receive new ones. This is easily achieved by building a one-dimensional lattice with connections between all agent pairs separated by κ or fewer lattice spacings, and creating a small-world network by choosing at random a small fraction r of the connections in the network and moving one end of each to a new agent, with that new agent chosen with probability proportional to its number of existing connections. This results in a distribution of the number of connections possessed by each agent i.e. a distribution of q_k, that is strongly skewed to the right. In fact, if the construction of the network is slightly modified so that new connections are added with preferential attachment (but no connections are removed), the distribution of q_k follows a power-law distribution, but a distribution with a non-zero probability of an agent having less than the modal number of connections seems more realistic in the context of word-of-mouth communication in marketing systems.

When an agent purchases a product, they inform each of the other agents in their circle with probability equal to $\Pr(spr)_{k^*} + |\delta_{ik^*}|$, where $\Pr(spr)_{k^*}$ is the basic propensity of agent k^* to spread word of mouth and δ_{ik^*} captures the extent to which the agent's most recent experience was satisfying or dissatisfying. Agents are thus more likely to spread word-of-mouth about products that they have just experienced as either very good or very bad. If an agent receives information on the same product from more than one agent, he or she selects the referral of only one of these agents, with selection probabilities proportional to $T_t(k^*, k)$, the degree to which previous referrals from k^* to k were successful i.e. resulted in satisfying experiences for agent k. Thus agents have the capacity to learn about the quality of other agents' referrals and use this information to accept or block future referrals. In this paper, we employ a learning condition in which $T_t(k^*, k)$ is multiplied by a factor of 0.1 following an unsatisfying referral and a factor of 3 following a satisfying referral. The asymmetry in the weighting is similar to that employed in [16], and is motivated by the fact that an unsatisfying referral is likely to be more reliable evidence that a referring agent k^* does not possess the same subjective preferences as agent k than a positive referral is of indicating the converse.

Other referral process are certainly possible, for example one integrating multiple sources of word-of-mouth rather than choosing only the most-trusted source: our main reason for employing the process described above is simplicity. Integrating different sources considerably complicates the process of learning about the trustworthiness of others, and raises further questions about the precise nature of the integration.

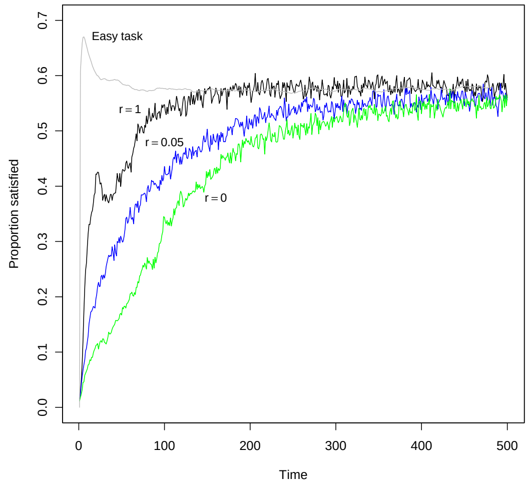
After determining who contacts whom, the actual referral is modelled as a transmittance of information about the perceived level of performance of an experience of product i^* from the referring agent k^* to the accepting agent k i.e. $p_{i^*j}(a_k, f_j(b_i), t)$ takes on the value $p_{i^*j}(a_{k^*}, f_j(b_i), t-1), \forall j$, provided that agent k is not currently using i^*. Information about other products is not transmitted, and an agent will ignore any word-of-mouth about the product he or she is currently using. In effect, the referral creates an *expected* level of performance in the mind of an accepting agent for the product referred to, which that agent may then use when making choice decision in subsequent time periods using the decision processes outlined in the previous section. Once an agent has personally experienced a product, any expected performance levels suggested by previous referrals are replaced by the experienced (subjective) performance levels $s_{ij}(a_k, f_j(b_i)) + \epsilon_{jkt}$ and $T_t(k^*, k)$ is adjusted depending on whether the experience was a satisfying one or not.

4. EXPERIMENTAL RESULTS

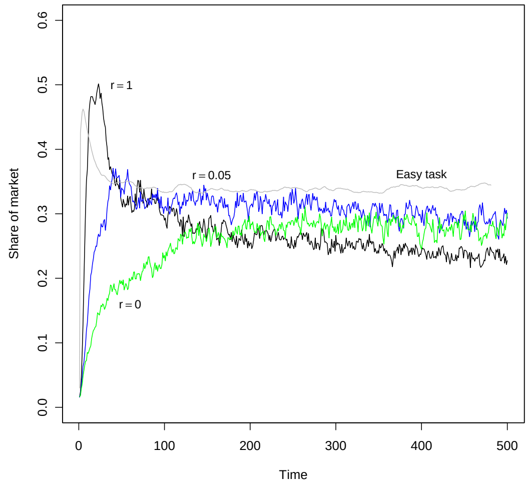
We examine the behaviour of a system of 200 agents consisting of three groups of 67, 67, and 66 agents respectively. Agents in each of the three groups have homogeneous subjective opinion functions S_{ij}. Simulations were run for 500 time periods, and twenty repetitions of each condition were used in order to generate aggregate results.

4.1 Choice task difficulty

We begin by examining the effect of task difficulty on the ability of various network configurations to converge to a state in which an acceptable proportion of the population are satisfied. In the 'easy' choice condition, there are 50 products to choose from in the market, evaluated over 4 attributes with all satisfaction thresholds set to 0.5 for all groups. There are therefore on average approximately 3 products that can be expected to satisfy any particular agent. In the 'hard' choice condition, there are 500 products to choose from in the market, still evaluated over 4 attributes but with all satisfaction thresholds now set to 0.7 for all groups, so there are on average approximately 4 products that can be expected to satisfy any particular agent. Locating a satisfactory product is therefore far more difficult under the 'hard' condition. The effect of task difficulty is evaluated on three network structures corresponding to $r = 1$ (random network), $r = 0.05$ (small-world network), and $r = 0$ (tight 'communities' of agents), with results shown in Figure 1 for the case of $\kappa = 3$.



(a) Proportion of agents satisfied



(b) Market share for leading product

Figure 1: Moderating effect of task difficulty on relationship between network structure (r) and system behaviour

Given a relatively easy task, the system very quickly i.e. in little over 50 time periods, converges to a state in which just less than 60% of agents are satisfied at any one time. Furthermore, different network structures have very little influence on results, so that only a single (smoothed) series is given for comparison with the 'hard' condition. Clearly, there are enough agents independently solving the task i.e.

finding a satisfying brand, to make the dissemination of information relatively independent of the ways in which connections are made. However, when it is more difficult to locate a satisfying product, the structure of the network becomes integral to the speed at which the system converges to a stable state. Importantly, the overall satisfaction level to which the system converges remains just below 60% regardless of which network structure is used, but convergence is considerably speeded by the random rewiring of even a small proportion of connections. Thus while the random network ($r = 1$) converges quickest, the small-world network ($r = 0.05$) also shows a substantial improvement over the tight communities represented by the one-dimensional ring lattice. This effect of the rewiring parameter r is much less pronounced for more highly-connected networks (e.g. $\kappa = 9$), which suggests that the degree distribution of a network is a more important determinant of system behaviour than the way in which agents are connected to one another.

Similar results are observed when looking at the market share achieved by the market leading product under each level of choice difficulty: market share is essentially independent of network structure for the easy task, with average share converging quickly to around 35%. Set a more difficult task, the convergence of market share to an approximate long-run equilibrium is in fact fastest for the small-world network, with the random and tight community networks taking different paths but similar times to reach their equilibrium levels. Also interesting is the finding that equilibrium market shares for the market leader appear to be slightly (of the order of 5–10%) higher when network connections are non-random – the random network seems to suffer more from the effects of habituatation than the other networks as a result of the rapid early adoption of the market leading product.

4.2 Market barriers

In the remainder of this paper we focus on the effect of various forms of market barriers on the ability of a system of agents to reach a state of acceptable satisfaction. For simplicity, we concentrate on the smaller set of 50 products i.e. the 'easy' choice task discussed above, but vary the number of connections that each agent begins with in order to simultaneously investigate the effect of degree distribution on system behaviour. Tables 1 and 2 show the effect of different degree distributions on the equilibrium proportion of agents that are satisfied at any one time, and the equilibrium proportion of agents switching products ("moving") in any one time period, under various levels of market barriers constraining their behaviour. In these two tables, equilibrium results have been calculated by averaging over time periods 450 to 500, when the system is in equilibrium or extremely close to equilibrium (Table 3 and 4 make use of all time periods).

	No WoM	$\kappa = 1$	$\kappa = 3$	$\kappa = 9$
$\beta = 0$	0.27	0.44	0.56	0.58
$\beta = 0.05$	0.26	0.39	0.50	0.52
$\beta = 0.2$	0.14	0.27	0.32	0.34
$\beta = 0.4$	0.07	0.17	0.22	0.25

Table 1: Effect of degree distribution and market barriers on proportion of market satisfied

	No WoM	$\kappa = 1$	$\kappa = 3$	$\kappa = 9$
$\beta = 0$	0.74	0.51	0.45	0.45
$\beta = 0.05$	0.66	0.43	0.38	0.37
$\beta = 0.2$	0.41	0.21	0.21	0.21
$\beta = 0.4$	0.17	0.09	0.09	0.09

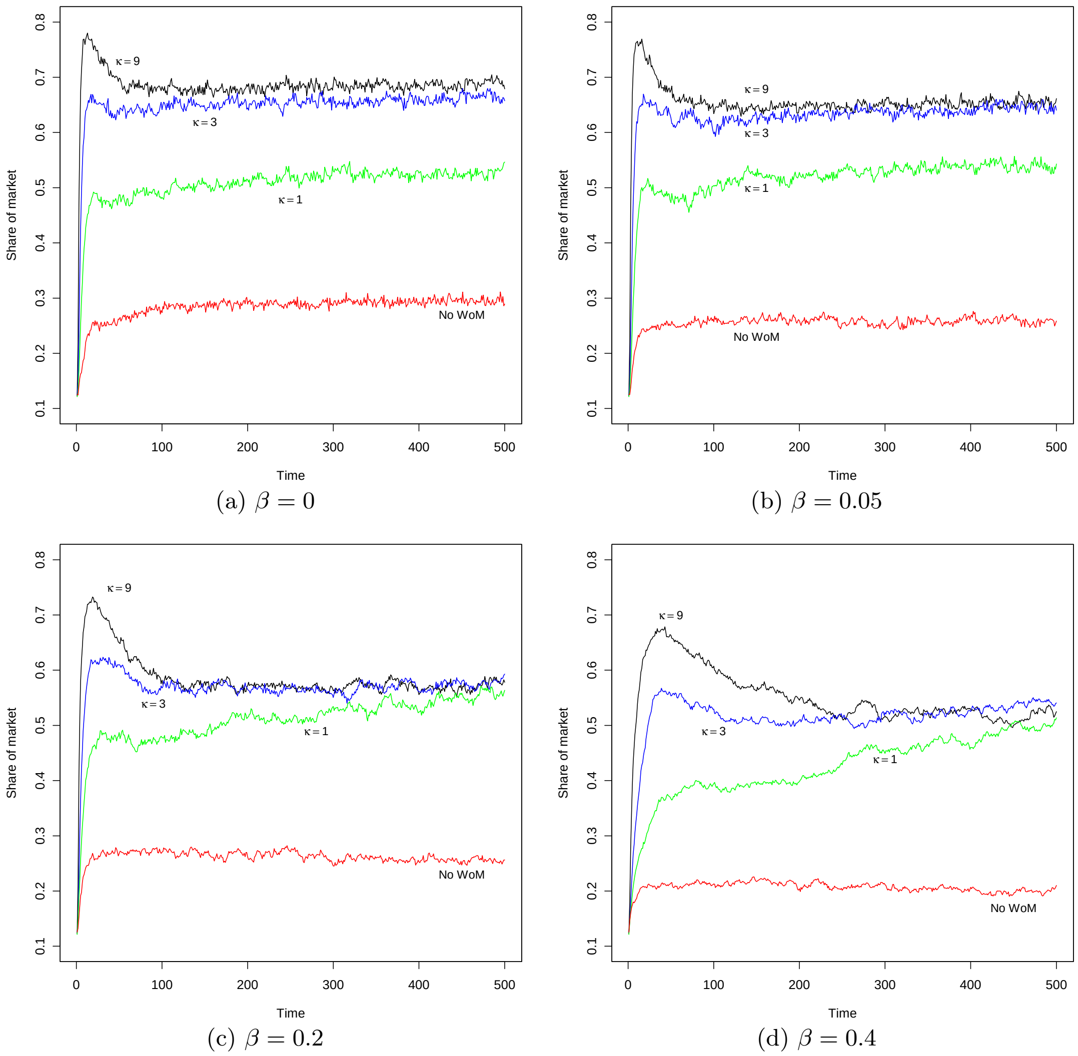
Table 2: Effect of degree distribution and market barriers on proportion of market moving

Three aspects are worth noting. Firstly, there is a strong diminishing marginal return of additional connections beyond a small number. The first few connections one makes increases the probability of finding a satisfying product 60% from 0.27 to 0.44 (for the first two contacts), followed by a further increase of roughly 25% to 0.56 for the next four. In contrast, adding a further 12 contacts improves relative satisfaction levels by less than 4%. Secondly, word-of-mouth communication continues to play an important role in improving the performance of the system even when market barriers are high. In fact, the role may even be more important in constrained conditions, since the relative gains obtained from word-of-mouth are greater the higher market barriers are – just having two contacts more than doubles the aggregate satisfaction level under the most extreme barriers ($\beta = 0.4$). Finally, it is clear that the mechanism by which barriers reduce satisfaction is by restricting movement (reflected in the lower proportion of agents moving in any particular column of Tables 1 and 2), but that increases in degree distribution act to *increase* satisfaction by precisely the same mechanism of reducing movement – this time by reducing the average amount of time required to find a satisfying brand.

	Positive referrals			Negative referrals		
	$\kappa = 1$	$\kappa = 3$	$\kappa = 9$	$\kappa = 1$	$\kappa = 3$	$\kappa = 9$
$\beta = 0$	0.21	0.93	3.27	0.00	0.00	0.00
$\beta = 0.05$	0.19	0.85	2.96	0.06	0.19	0.60
$\beta = 0.2$	0.13	0.57	2.04	0.30	0.92	2.83
$\beta = 0.4$	0.08	0.40	1.49	0.60	1.81	5.44

Table 3: Median number of positive and negative referrals made per agent per time period

Perhaps the most interesting effects exerted by market barriers are those exerted over the market shares of leading products. Figure 2 shows the cumulative market share captured by the top three products in the market over time, for all types of market barriers using different degree distributions. Again, two comments can be made. Firstly, in the absence of market barriers, a greater proportion of the market is captured by the market leading products when markets are highly-connected relative to when they are poorly-connected. This difference can amount to as much as 15%, and is explained by positive feedback within the more highly-connected networks that serves to increase the probability that, once a set of satisfying products have emerged, one is kept informed about these leading products because at least one of one's contacts is using it. Secondly, the relatively higher market share enjoyed by market leaders in highly-connected networks is eroded by market barriers. In moving from $\beta = 0$ to $\beta = 0.2$ to $\beta = 0.4$, market leaders collectively lose an absolute share of 15% and 10% under the larger degree distributions $\kappa = 9$ and $\kappa = 3$ respectively.



(a) $\beta = 0$ (b) $\beta = 0.05$

(c) $\beta = 0.2$ (d) $\beta = 0.4$

Figure 2: Effect of market barriers on the share of the market captured by the leading 3 products

In contrast, no change in collective market share is observed when $\kappa = 1$, although convergence to equilibrium conditions is slower. It seems reasonable to suggest that increases in negative word-of-mouth, which occurs when an unsatisfied agent is prevented from switching to another product, are particularly damaging to leading products when agents are well-connected, and that under moderate to strong market barriers these effects more than offset any gains achieved by the spread of positive word-of-mouth through the network.

Table 3 displays the number of attempted referrals, both positive and negative, as a function of degree distribution and extent of market barriers, and shows that stronger market barriers act to simultaneously depress positive word-of-mouth communication and increase negative communication from those trapped in unsatisfying product relationships, and that this effect is particularly pronounced for more highly-connected networks. The reduction in the number of positive referrals as market barriers impose increasingly severe constraints is also reflected in Table 4, which shows the median number of product trials each agent makes per time period based on a referral from another agent. Whereas under few or no barriers agents in a highly-connected network make substantially more reference-based product trials than agents in poorly-connected networks, when barriers are severe both types of network carry only very little positive referral information. This clearly has a relatively greater impact on the highly-connected network, which relies on the spread of positive referral information to achieve higher satisfaction levels. Moreover, this result might be even stronger in reality if agents in poorly-connected networks attempt to compensate for the relative sparcity of connections by making more forceful or persuasive referrals where they do occur.

	$\kappa = 1$	$\kappa = 3$	$\kappa = 9$
$\beta = 0$	0.13	0.27	0.35
$\beta = 0.05$	0.11	0.22	0.28
$\beta = 0.2$	0.05	0.10	0.14
$\beta = 0.4$	0.02	0.05	0.06

Table 4: Median number of referrals leading to a product trial received per agent per time period

5. CONCLUSIONS AND RELATED WORK

Purchasing behaviour in many markets takes place on a substrate of networks of word-of-mouth communication across which agents exchange information about products and their likes and dislikes. Understanding the ways in which flows of word-of-mouth communication influence aggregate market behaviour requires one to study both the underlying structural properties of the network and the local rules governing the behaviour of agents on the network when making purchase decisions and when interacting with other agents. These local rules are often constrained by the nature of a particular market, or else imposed by strategic suppliers or social customs. The proper modelling of a mechanism for word-of-mouth transmittal and resulting behavioural effects thus requires a consideration of a number of complex and interacting components: networks of communication, source credibility, learning processes, habituation and memory, external constraints on behaviour, theories of information transfer, and adaptive behaviour. In this paper we have attempted to address some of these issues in a manner which reflects how agents might act in the real world.

Using the key notions of a limited communication network, a simple learning process, and a satisficing heuristic that may be subject to external constraints, we showed (1) the importance of word-of-mouth communication to both system effectiveness and stability, (2) that the degree distribution of a network is more influential than the way in which agents are connected, but that both are important in more complex environments, (3) that rewiring even a small number of connections to create a small-world network can have dramatic results for the speed of convergence to satisficing distributions and market share allocations, (4) that word-of-mouth continues to be effective when movements between products are constrained by market barriers, and (5) that increases in negative word-of-mouth incurred as a result of market barriers can reduce the market share collectively captured by leading brands, but that this is dependent on the existence of a suitably well-connected network structure.

It is the final finding that is likely to be most surprising and practically relevant for the marketing research field, and suggests that it may not always be in the best interests of a market leader to impose barriers that prevent customers from leaving. In poorly-connected networks, the effect of barriers on market shares is slight. In contrast, in well-connected networks, negative word-of-mouth can prevent agents from trying a product that they might otherwise have found satisfying, and this can inflict significant harm on market share. Products with small market share (which, in the context of our simulations, is generally due to the product offering poor performance) are relatively unaffected by negative word-of-mouth, since most product trials are likely to be unsatisfying in any case.

Agent-based modelling provides a natural way for beginning to investigate the types of dynamics that occur in marketing systems. Naturally the usefulness of results is for the most part dependent on the quality of the modelling of the two 'modules' comprising network structure and local behaviour. On the network side, future work might investigate the relationship between degree distributions, the way connections are created and destroyed over time, whether preferential attachment is influential, and the extent to which social identity informs network strucutre, all in larger networks of more heterogenous agents. On the behavioural side, one might look at the adaptation of satisfaction thresholds during the course of communication, responses to systematic changes in product performances over time, the integration of various information sources, and different market barrier structures. All these areas provide fascinating opportunities to introduce psychological realities into models of marketing systems and to observe the resulting behaviour of the system under increasingly realistic scenario descriptions.

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