Marketing Letters 12:3, 211–223, 2001

Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth

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Received November 2000; Revised February 2001; Accepted February 2001

Abstract

Though word-of-mouth (w-o-m) communications is a pervasive and intriguing phenomenon, little is known on its underlying process of personal communications. Moreover as marketers are getting more interested in harnessing the power of w-o-m, for e-business and other net related activities, the effects of the different communications types on macro level marketing is becoming critical. In particular we are interested in the breakdown of the personal communication between closer and stronger communications that are within an individual's own personal group (strong ties) and weaker and less personal communications that an individual makes with a wide set of other acquaintances and colleagues (weak ties).

We use a technique borrowed from Complex Systems Analysis called *stochastic cellular automata* in order to generate data and analyze the results so that answers to our main research issues could be ascertained. The following summarizes the impact of strong and weak ties on the speed of acceptance of a new product:

- The influence of weak ties is at least as strong as the influence of strong ties. Despite the relative inferiority of the weak tie parameter in the model's assumptions, their effect approximates or exceeds that of strong ties, in all stages of the product life cycle.
- External marketing efforts (e.g., advertising) are effective. However, beyond a relatively early stage of the growth cycle of the new product, their efficacy quickly diminishes and strong and weak ties become the main forces propelling growth. The results clearly indicate that information dissemination is dominated by both weak and strong w-o-m, rather than by advertising.
- The effect of strong ties diminishes as personal network size decreases. Market attributes were also found to mediate the effects of weak and strong ties. When personal networks are small, weak ties were found to have a stronger impact on information dissemination than strong ties.

Key words: word-of-mouth, social networks, cellular automata, complex systems

Word-of-Mouth (w-o-m) communications is a pervasive and intriguing phenomenon. It has been generally found that both satisfied and dissatisfied consumers tend to spread positive and negative w-o-m, respectively, regarding products and services which they purchase and use (Anderson 1998). The significant role of w-o-m in the dissemination of market information is supported by broad agreement among practitioners and academics. A long list of academic scholarship, industry market research and anecdotal evidence points to the significant affect of w-o-m on consumer behavior and, consequently, on sales (e.g., Eliashberg, Jonker, Sawhney and Wierenga 2000; Krider and Weinberg 1998; Buttle 1998; Dabaher and Rust 1996; Reichheld 1996; Herr, Kardes and Kim 1991; Mahajan, Muller and Kerin 1984). Evidence also indicates that consumers' decision making is strongly influenced by w-o-m. Over 40% of all Americans actively seek the advice of family and friends when shopping for services such as doctors, lawyers and auto mechanics (Walker 1995). W-o-m has also been found to constitute a major input to the deliberations of potential consumers regarding the purchase of new products (Rogers 1995).

Recognition of the significance of w-o-m, coupled with growing reservations regarding the effectiveness of commonly used forms of marketing communications, such as advertising (Rust and Varki 1996), may explain the repeated calls in the business press for managers to attend to the power of w-o-m (Wilson 1994; Griffin 1995; Silverman 1997). Today's managers are diverting increased efforts to the management of w-o-m. Recent anecdotal evidence confirms an upward trend in the use of referral reward programs, in which customers are compensated for "spreading the word" about a product, and inducing product consumption by their acquaintances (Biyalagorsky, Gerstner and Libai 2001). Diverse marketers, including museums (DeMasters 2000), book publishers (Cohen 1999) and movie producers (McCarthy 1999) have launched w-o-m campaigns with reported success.

Furthermore, the mounting use of the Internet, enabling surfers to communicate quickly with relative ease, has established the contemporary version of this phenomenon, known as "Internet w-o-m" or "word of mouse", as an important marketing communication channel. In what is sometimes labeled as "viral marketing", companies are currently investing considerable efforts to trigger a word of mouse process and accelerate its distribution (Schwartz 1998; Oberndorf 2000).

However, the current interest in w-o-m management has yet to succeed in transforming managers' entrenched perceptions of the w-o-m phenomenon as a "black box". Maintaining explicit or implicit beliefs that the personal influence process is beyond their control (Silverman 1997), managers hope, at the most, to "manage" rather than "direct" w-o-m effects. Unfortunately, as most academic research and writing on w-o-m in areas such as marketing or communications has concentrated on the individual or personal network level (e.g., Herr, Kardes, and Kim 1991; Gilly, et al. 1998; Brown and Reingen 1987), academic marketing research offers little to mitigate managers' sense of inefficacy. Unlike other areas of marketing communications, such as advertising, sales promotion or sales force (e.g., Boulding, Lee and Staelin 1994; Jeddidi, Mela and Gupta 1999), in which significant attention has been given to assessing aggregate effects on sales, little is known about how w-o-m aggregates to impact sales levels.

One cause of this gap in knowledge relates to the underlying complexity of the w-o-m process. The spread of information in a given social system may be described as "an adaptive complex system", i.e., a system that consists of a large number of individual entities which interact with each other (in what is sometimes an indiscernible manner), ultimately generating large-scale, collective visible behavior. Although the individual interactions may be simple in many such adaptive systems, the large scale of the system at work allows the emergence of patterns which are hard to predict, hard to track empirically, and are often almost impossible to analyze analytically (Waldorp, 1992).

Various disciplines, such as physics, biology and ecology, have developed theories and methods to investigate the evolution of complex systems. In the social sciences, which recognize the inherent complexity of many social systems such as markets and organizations, attention has recently been drawn to the analysis of complex systems, specifically in the fields of economic analysis (see Rosser 1999) and organizational management (e.g., Anderson 1999). However, this trend is still in its infancy, and research activity has yet to invest in the question of how micro-level w-o-m activity governs macro-level effects.

Here, we offer a technique for linking w-o-m micro- and macro-phenomena, employing *stochastic cellular automata*, a tool for complex system analysis. Cellular automata models are simulations of aggregate consequences, based on local interactions between individual members of a population. In the case of w-o-m, these local interactions are diverse types of interpersonal interactions. In the specific model presented here, we concentrate on the emergence of macro-effects from micro-effects, based on one of the fundamental theories of communications, known as the “strength of weak ties” (Granovetter 1973).

1. Weak and Strong Ties

The theory of “the strength of weak ties” (Granovetter 1973) offers one of the most important conceptual explanations of the process by which micro-level interactions affect macro-level phenomena. Granovetter claimed that individuals are often influenced by others with whom they have tenuous or even random relationships. These influences are labeled “weak ties”, to distinguish them from the more stable, frequent and intimate “strong tie” interactions that characterize individuals’ personal networks. Although weaker in absolute impact on the individual level, the significance of weak ties lies in their potential to unlock and expose interpersonal networks to external influences (individuals in distant networks), thus paving the path for the spread of information throughout society.

Since its publication, Granovetter’s theory has been the object of repeated inquiry, albeit primarily in contexts not directly related to marketing research, such as job searches or migration patterns (e.g., Bian, 1997; Wilson, 1998). Adopting a consumer research orientation, Brown and Reingen (1987) generally found support for the focus on the two types of w-o-m ties proposed by Granovetter. They found that although strong ties were more likely to be activated and perceived as influential in consumers’ decisions, weak ties were more likely than strong ties to facilitate w-o-m referral flows. Duhan et al. (1997) also found support for these two distinct paths of influence, noting that factors such as consumers’ previous knowledge or perceived task difficulty affect consumers’ information reception from different sources. Other empirical work found that when ties are strong, w-o-m receivers are more likely to actively look for information and that the w-o-m information will have a significant influence on the receiver's purchase decision (Bansal and Voyer 2000). However, Rogers (1995) suggests that even given the stronger information flow within strong ties, weak ties play a crucial role in the spread of information by word-of-mouth on the aggregate level, especially about innovations.

While it is clear that weak and strong ties may be conceptualized as two distinct paths of information dissemination, we know little about their macro-effects. For example, we lack any comparative data on the respective rates of dissemination of these two mechanisms, nor do we know how they interact with other marketing efforts such as advertising. Given the increased efforts to "manage" w-o-m, improving our understanding of how these two major paths of w-o-m affect information dissemination should be of great interest to managers.

In our present study, we employ stochastic cellular automata to investigate the following questions:

1. *Which of the effects - strong ties, weak ties or marketing efforts - has more influence on the aggregate growth of information dissemination?*
   On the one hand, information is expected to pass more readily through strong ties, due to their larger frequency of activation and perceived reliability. However, weak ties are essential for initializing the information flows in distinct networks. What is the time-dependent relationship between these two forces?
2. *How do personal network size and quantity of weak ties affect the influence of strong and weak ties on the aggregate growth of information dissemination?*
   How do factors such as the number of weak ties contacts and network size (number of individuals in a typical personal network) mediate the consequential effects of weak and strong ties?
3. *How does advertising interact with strong or weak ties to affect the aggregate growth of information dissemination?*
   Which of the two types of w-o-m paths will be more highly impacted by the presence of marketing support such as advertising?

2. Cellular Automata

Cellular automata is a complex systems modeling technique, which simulates aggregate consequences based on local interactions between individual members of a population. Individual members in the model may represent plants and animals in ecosystems, vehicles in traffic, people in crowds or autonomous units in a physical system. The models typically consist of a framework in which interactions occur between various types of individuals. In stochastic cellular automata model, each individual's behavior is dictated by a predefined scheme of response probabilities and is a function of the state of other individuals with whom he interacts (see, for example, Holland 1995). The solution of such models consists of tracking the changing state of each individual over time. Thus, cellular automata is distinct from alternative modeling techniques that use individual attributes to calculate average population attributes and then simulate changes in the "average" population. For recent applications of complex systems models to marketing problems see Krider and Weinberg (1997), Goldenberg et al. (2000) and Goldenberg, Libai and Muller (2001).

Figure 1 depicts the cellular automata model graphically. The model consists of a finite number of virtual individuals in a given simulated social system, each of whom is able to receive information during consecutive, discrete periods. Social interactions in the system are of two types: proximal contacts among members of the same network and weak ties interactions with individuals belonging to different networks. We define two states of individuals: "informed" – those who have received the relevant information and are informed of the phenomenon – and "uninformed" – those individuals who have not received the information. The model makes use of the following additional assumptions:

1. Interpersonal contacts (β) are defined as the probability of an uninformed individual to be affected by an informed individual, in one period, i.e., change his/her state from "uninformed" to "informed". Subscripts *s* and *w*, respectively, differentiate interactions in which the source of the information belongs to the individual's network or to a different network. Reflecting theory and previous research (e.g., Brown and Reingen 1987) β_s is larger than β_w. Thus, the probability of an individual to be affected by other individuals in his own network is greater than the probability of changing his state from uninformed to informed as a result of contacts with other, weak ties individuals.
2. Each individual "belongs" to a single personal network. Each network consists of individuals who are connected by strong ties (β_s). In each period, individuals also conduct a finite number of weak ties interactions with individuals outside their personal networks (β_w).

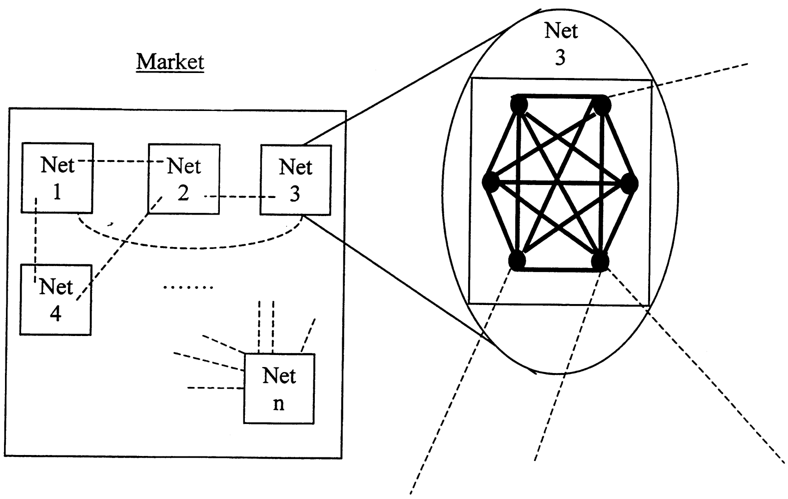

Figure 1. Market with Personal Networks. Strong Ties (β_s) are Depicted with Solid Lines while Weak Ties (β_w) are Depicted with Dotted Lines.

3. Uninformed individuals also have a one period probability, α, of becoming informed through their exposure to other marketing efforts, such as advertising. Following the w-o-m literature (e.g., Buttle, 1998), the probability of being affected by advertising exposure is assumed to be smaller than the effect of a w-o-m contact. Although the present model incorporates advertising, other mass media sources of marketing information are hypothesized to have a similar effect.

In the first stage of the analysis, we define the range of the individual level parameters to be analyzed by a computer program (written in C for this study). The program both generates individual level data and aggregates these results to plot macro-level adoption curves. In the second stage of analysis, individual level and aggregate level data are fed into a statistical program (SAS) to perform the necessary statistical analyses to identify main effects.

We divide the entire market equally into personal networks, in which each individual can belong to one network. In addition, in each period every individual conducts random meetings with other individuals external to his personal network.

Thus if in period t, an individual is connected to m informed others belonging to his or her personal network and j informed others who are random contacts represented by weak ties, the probability of the individual becoming informed in period t, is given by:

$$p(t) = (1 - (1 - \alpha)(1 - \beta_w)^j(1 - \beta_s)^m) \tag{1}$$

The following step-by-step outline describes the cellular automata algorithm:

Period 0: This is the initial condition where all individuals are uninformed (receiving the value of 0)

Period 1: The probabilities for each individual (given by equation 1) are realized. Clearly only advertising is at work in this period as word-of-mouth needs informed individuals to start the process. A random number U is drawn from a uniform distribution in the range [0,1]. If U $<$ *p(t)* then the individual moves from non-informed to informed (receiving the value of 1). The individual stays non-informed otherwise.

Period 2: The informed individuals begin the w-o-m process by deploying their strong ties within their own personal network, and weak ties to other networks. Probabilities are realized as in step 1, and the random number is drawn so that when U $<$ *p(t)* the individual moves from non-informed to informed.

Period n: This process is repeated until 95% of the total market (3000 individuals) becomes informed.

3. Method

All combinations of the parameters were considered in a full factorial design experiment. Each of the five input variable parameters was manipulated on seven levels, to produce overall

$7^5 = 16{,}808$ information dissemination process simulations. Each process was terminated when 95% of the population attained informed status. Parameter ranges were set as follows:

1. Size of each individual's personal network	5–29
2. Number of each individual's weak ties contacts	5–29
3. Effect of weak ties (β_w)	0.005–0.015
4. Effect of strong ties (β_s)	0.01–0.07
5. Effect of advertising (α)	0.0005–0.01

Note that since weak and strong ties effects represent probabilities, their absolute value range determines the magnitude of a "period", which is less of an interest to us. Our interest lies with the *relative* values of the parameters analyzed. Consistent with previous literature as specified above, we set the advertising effect to be in a range that is lower than the range of the w-o-m effects. In addition, the weak ties probabilities are set to be lower than the strong ties probabilities. Networks size range were set to reflect a reasonable range of personal contacts, and while the ranges of weak ties and strong ties contacts are the same, through the simulation we can analyze the effect of different combinations of their sizes.

After generating all possible outcomes of the above manipulations, a number of analyses were conducted to explore the relationship between weak and strong ties and the rate of information dissemination. One possible aggregate level measure, *All Informed*, is the number of periods elapsing before 95% of the population becomes informed. However, cellular automata modeling enables us to extend our examination and discover more complex, perhaps non-linear, effects, by observing the succession of changes occurring over the life-span of the process. More specifically, to understand how the respective impacts, weak and strong ties, evolve over the different stages of the process, we look at *Early Informed, Middle Informed* and *Late Informed* - variables reflecting the number of periods elapsing before 0–16%, 16–50% and 50–95% of the market become informed. We denote the time from the onset of the process until 16% of the market has attained "informed" status as T_0–$T_{16\%}$ and so forth. Three OLS regressions, designed to relate aggregate level measures to micro-level parameter values, were conducted, with *Early Informed, Middle Informed* and *Late Informed* respectively as the dependent variables, and the network and influence parameters outlined above as the dependent variables. Regression results presenting the effects of the different communication parameters are given in Table 1. We also examined the impact of the interactions between the size of personal networks, the number of weak ties and advertising, on the one hand, and weak and strong ties on the other. This was done by running an OLS regression for each factor value and the other four parameters as independent variables, with *All Informed* as the dependent variable. Results are given in Figures 2–4.

4. Results

The following main results raised some interesting observations:

Result 1: The influence of weak ties on the speed of information dissemination is at least as strong as the influence of strong ties.

Table 1. A Comparison of the Effects of Weak and Strong Ties on the Speed of Information Dissemination (The Dependent Variable is the Number of Periods Comprising Each Process Stage, the OLS Parameters are Standardized)

	T_0–$T_{16\%}$	$T_{16\%}$–$T_{50\%}$	$T_{50\%}$–$T_{95\%}$
Strong ties effect	−0.25	−0.33	−0.37
Weak ties effect	−0.26	−0.40	−0.38
Advertising effect	−0.61	−0.11	−0.04
Adjusted R^2	0.66	0.60	0.63

All variables are significant at $p \leq 0.0001$ level.

Despite the relative inferiority of the weak tie parameter in the model's assumptions (strong ties reflect a greater probability for an individual-level transformation), their effect approximates or exceeds that of strong ties, in all three process stages (see Table 1). These results challenge the emphasis placed, in most of the research on w-o-m, on strong ties as the important means of information dissemination (Brown and Reingen, 1987) and provide quantitative support for Granovetter's theory (1973) in this regard. However, recalling our conceptualization of the market as a complex system, these results should not cause us excessive surprise. Like most complex systems, interactions and non-linear effects may be present beneath the surface.

While this finding is intriguing at all stages of the information growth process, the increasing importance of the effect of weak ties during the middle stage ($T_{16\%}$–$T_{50\%}$) suggests that their significance stems from their unique effect on growth, rather than from their prevalence. Define "activated networks" as networks containing at least one informed individual. Closely tracking the dynamics of the process reveals that the initially large proportion of uninformed individuals in activated networks gradually decreases as more individuals become informed in each network. Since the impact of strong ties is related to the ratio of uninformed to informed individuals in each network, as more individuals become informed, the potential effect of strong ties is gradually exhausted. When all members of activated networks become informed, the effect of strong ties is contingent upon on the activation of new networks, a task performed by the weak ties. The increasing slope of the effect of the weak ties between the first and middle stages thus reflects the fact that the successive activation of new networks through weak ties enables the continuation of the process.

Result 2: Beyond a relatively early stage of the process, the effect of external marketing efforts (e.g., advertising) quickly diminishes and strong and weak ties become the main forces propelling the process.

The results clearly indicate that information dissemination is dominated by both w-o-m paths, rather than by advertising. This confirms findings from the diffusion of innovation literature, which pointed to w-o-m as the main factor driving the speed of innovation diffusion (Rogers 1995; Mahajan, Muller and Srivastava 1990).

Moreover, the results in Table 1 also provide quantitative support for Rogers' (1995) argument that, while advertising may be important in the initial stages of information dissemination, the main mechanism driving innovation diffusion after product takeoff is w-o-m.

Our findings show how the major role of marketing efforts in the initial stage of the process (their impact is twice as powerful as that of either the strong or weak ties) diminishes after 16% of the market becomes informed. When information dissemination reaches the halfway mark (i.e., 50% of all individuals are informed), the impact of marketing efforts diminishes further, to one-third and one-quarter of the impact of strong ties and weak ties, respectively. Although in the initial stage, strong and weak tie effects were almost equal in potency, weak ties have a larger effect than strong ties, relative to the advertising effect, in the second stage of the process.

Result 3: The effect of strong ties on the speed of information dissemination diminishes as personal network size decreases.

Market attributes were also found to mediate the effects of weak and strong ties, as this and the following results show. When personal networks are small, weak ties were found to have a stronger impact on information dissemination than strong ties. A non-linear relationship between weak ties and network size was indicated (see Figure 2).

Result 4: As the number of weak ties contacts increases, the effect of strong ties decreases while the effect of weak ties increases (see Figure 3).

Result 5: As the level of advertising increases, the effects of both strong and weak ties are marginally impacted, in inverse directions: the effect of strong ties increases while the effect of weak ties decreases (see Figure 4).

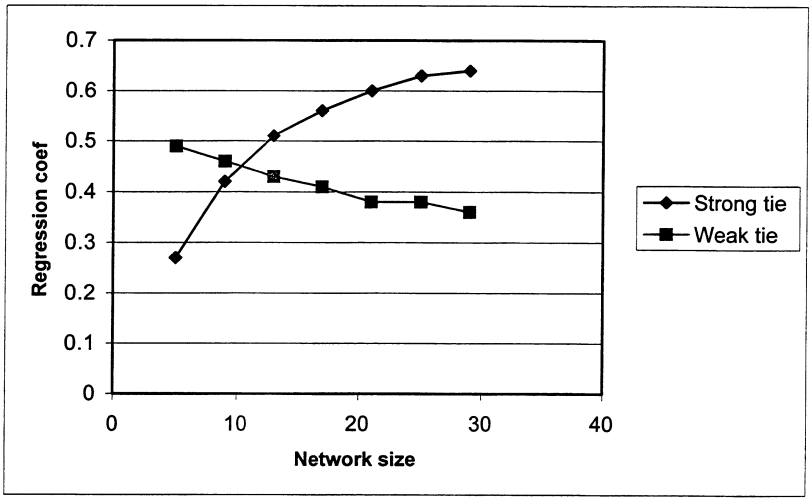

Figure 2. The Effects of Strong and Weak Ties on Speed of Information Dissemination as a Function of Personal Network Size.

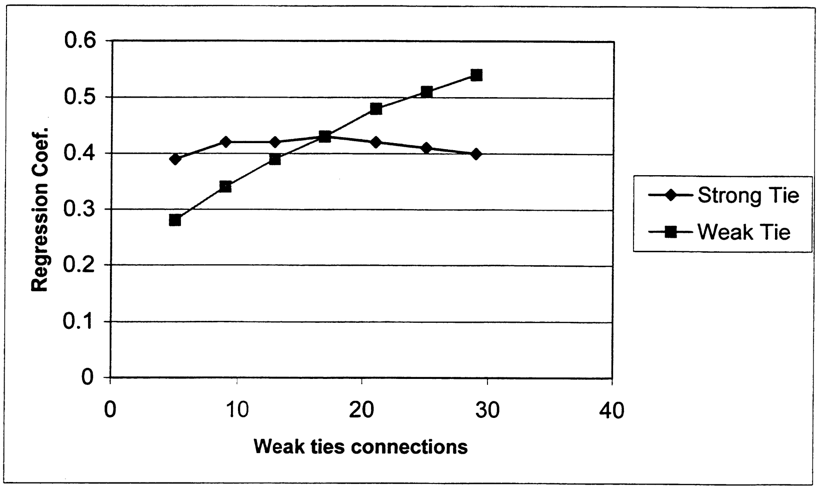

Figure 3. The Effects of Strong and Weak Ties on Speed of Information Dissemination as a Function of the Number of Weak Ties Contacts.

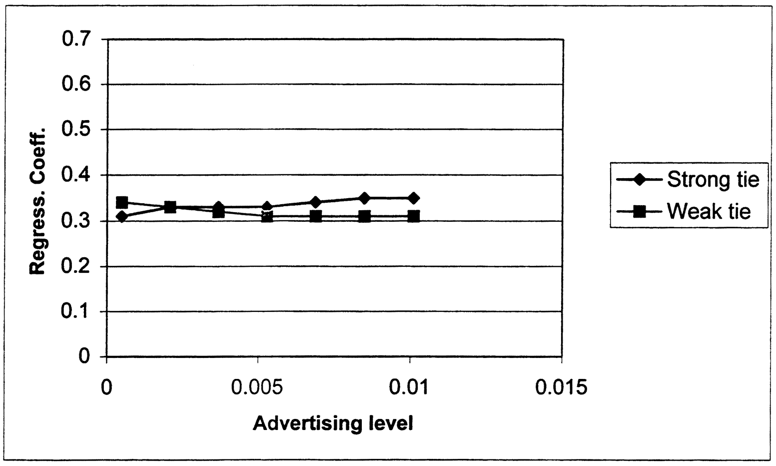

Figure 4. The Effects of Strong and Weak Ties on the Speed of Information Dissemination as a Function of Advertising.

5. Discussion and Implications

In the present study, we demonstrated how complex systems analysis (stochastic cellular automata in our case) contributes to our understanding of the aggregate level effect of weak and strong social ties, in terms of the spread of information through word-of-mouth. First, as Table 1 demonstrates, for the range of parameters examined here, weak ties have an influence on information dissemination, which is at least equal to that of strong ties. Second, both types of social effects have a stronger influence on information dissemination than the effect of advertising.

As shown in Figures 2–4, the relative effects of strong and weak ties may depend on other factors, such as personal network size, number of weak ties interpersonal interactions characterizing a social system, and advertising. When network size is small, or weak ties contacts are numerous, or advertising effect is weak, weak ties may have a greater impact on the rate of information dissemination than strong ties.

These results have important managerial implications. Managers attempting to influence w-o-m spread should distinguish between the two kinds of social interactions that contribute to both positive and negative w-o-m communications. For example, in certain situations managers may want to distinguish referral rewards for referrals of close friends and family members from rewards for referring others. When personal networks are large, weak ties contacts among inter-network individuals are few, or the advertising effect is strong, fostering inter-network ties may be one of the few options available to marketers. Moreover, as findings from the diffusion of innovations literature suggest, w-o-m and advertising effects may differ among different market segments (Rogers and Kincaid, 1981; Rogers, 1995). Marketers are advised to develop market research, which would provide estimates of these factors for different segments and products.

While this study adds to our knowledge by exploring the aggregate level effect of weak and strong w-o-m ties, we recognize its limited scope, especially considering the wide range of analyses enabled by cellular automata methods for the exploration of phenomena such as w-o-m. This technique, due to its unique features and especially the ability to model a wide variety of market situations, is suited to model many marketing phenomena that have been traditionally under-researched. We believe it is especially suited to analyze interpersonal based processes such as the growth of new products and other w-o-m based social phenomena that have been only partially explored due to the complexity inherent in these processes. Where diffusion of innovations modelers are often restricted by simplifying assumptions, cellular automata enables us to deeply explore real life phenomena that are not analytically tractable. It is especially suited to model individual level heterogeneous behavior where the aggregation is done by the program itself without having to resort to simplifying assumptions needed for the aggregation.

For example, such methods may be used to explore web-based information dissemination or the consequences of diverse "viral marketing" approaches using w-o-m channels such as "chat rooms", websites of various sizes containing links to other sites, large-scale information transmission though e-mail lists and web-based referral reward programs. Other non-web examples include an analysis of time-based changes of marketing mix and consumer behavior variables for new product growth (e.g., price, advertising, repeat purchase, market potential), the optimal marketing in the presence of network externalities or the optimal marketing to early and mainstream markets for high-tech products. Considering the options complex system methods such as cellular automata open for researchers, it is clear that this is just a short list for promising future research.

Acknowledgements

The authors would like to thank Moshe Givon, John Hogan, David Mazursky, Charles Weinberg and two anonymous reviewers for their insightful comments and suggestions. This research was supported by The Israel Science Foundation founded by the Israel Academy of Sciences and Humanities and by grants from the K-mart International Center of Marketing and Retailing, and Davidson Center at the Hebrew University and the Israeli Institute for Business Research ar Tel Aviv University.

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