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## The NPV of bad news

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### Abstract

We explore the effects of individual-and network-level negative word-of-mouth on a firm's profits using an agent-based model, specifically an extended *small-world* analysis. We include both permanent strong ties within the social network, and changing, often random, weak ties with other networks. The effect of negative word-of-mouth on the Net Present Value (NPV) of the firm was found to be substantial, even when the initial number of dissatisfied customers is relatively small. We show that the well-known phenomenon of the strength of weak ties has contradictory effects when taking into account negative word-of-mouth: Weak ties help to spread harmful information through networks and can become a negative force for the product's spread.

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### 1. Introduction

Consider the following actual case of a consumer electronics company that recently introduced a new audio CD protection device. Soon after launch, the company discovered that the product performed poorly in about 2% of the European market. Fixing the problem was not simple, and the firm's executives debated how much the company should invest to mitigate the problem. Some argued that 2% of the market would have negligible economic consequences. Others countered that the dissatisfied customers who could not be identified in advance would generate negative word-of-mouth communications following their poor experience, ultimately harming the firm's profits. Even though the executives were aware of the conventional wisdom that "bad news travels fast", none of them had a good grasp as to how to assess the possible effects of the anticipated negative word-of-mouth on their profits.

Unfortunately, there is little in the literature that can help managers in such cases. Marketers do realize that negative word-of-mouth communications can considerably lower a firm's profits. Thus, considerable attention has been given in the academic literature to explore topics such as the circumstances under which consumers spread negative word-of-mouth (Richins, 1983), the quantity of negative word-of-mouth that dissatisfied consumers spread (Anderson, 1998), and the relative weight of negative information received by consumers as compared to positive information (Mizerski, 1982).

Similarly, there are numerous anecdotal stories in the business literature about the possible harm caused by a dissatisfied customer's word-of-mouth communications (Hart, Heskett, & Sasser, 1990). Recently, negative word-of-mouth has drawn additional interest, as marketers have become more aware of the speed at which negative product-related information can pass through electronic means such as the Internet (Ritson, 2003; Ward & Ostrom, 2006).

Yet there is scant formal analysis in academic studies that can help managers understand the economic implications of negative word-of-mouth. While considerable literature has dealt with negative word-of-mouth at the individual or network level (see Buttle, 1998 for a review of the word-of-mouth literature), and some have analyzed negative word-of-mouth at the aggregate level (Mahajan, Muller, & Kerin, 1984), little is

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known about how both levels combine to produce market-level results. Tying both ends together is essential, as managers will typically be able to collect information on the determinants and extent of negative word-of-mouth at the individual level, yet their interest in and ability to justify firm-level actions will ultimately lie in the analysis of aggregate-level financial results.

A possible reason for the dearth of formal analysis is that the spread of information in a social network is a complex system that consists of a large number of individual entities interacting with each other, in what is sometimes an indiscernible manner, ultimately generating large-scale, collective, visible, and quantifiable behavior (Anderson, 1999; Holland, 1995). In other words, negative word-of-mouth is an invisible force, leaving no tracks in the sales curves. Unlike the positive interactions of consumers that lead to adoption and growth of sales, we do not have reliable measures of the negative word-of-mouth that shrinks the market by transforming potential adopters into non-adopters.

In this study, we explore the effect of both individual-and network-level negative word-of-mouth on aggregate sales using an agent-based modeling approach, specifically an extended model of *small-world* analysis (Watts, 1999). Utilizing a *dynamic small-world* approach, we simulate a market in which information spreads when consumers interact with each other, using both strong ties within their own social system and weak ties with other networks (Granovetter, 1973).

Our analysis explores the effects of changes in a social system's information structure, the intensity of strong and weak ties, and marketing effects, as well as determinants of negative word-of-mouth phenomenon, such as the strength of negative word-of-mouth compared to positive word-of-mouth or the number of disappointed customers, on the aggregate sales and net present value of the cash flow that marketers can hope to achieve.

An important point to note is that our approach deals with negative word-of-mouth more than with other possible negative effects of contagion. While the internal influence parameter of the aggregate diffusion models is often interpreted to represent word-of-mouth, it can also capture imitation effects such as social learning, social pressures, or network effects (see Van den Bulte & Stremersch, 2004). Based on a meta-analysis of aggregate diffusion models, Van den Bulte and Stremersch even suggest that imitation effects may be stronger overall than word-of-mouth effects in the growth of markets for new products.

Positive contagion effects in aggregate diffusion models may thus include both imitation effects and word-of-mouth. Yet the picture for negative word-of-mouth is different. In the modeling approach that we present, negative word-of-mouth stems from individual customer dissatisfaction, and the effects are manifested at the network level. Negative contagion effects may not be a product of dissatisfaction, but rather the mere adoption by other consumers, who, for example, belong to a segment of the population whose adoption reduces the social utility of the product. For example, Joshi, Reibstein, and Zhang (2006) reported a negative contagion effect of the adopters of the Porsche SUV (Cayenne) on the potential adopters of traditional Porsche roadsters. This effect requires specific modeling of

segmentation and contagion that will capture these segment-based phenomena. For example, unlike word-of-mouth, observational learning does not demand direct contact, so that negative contagion can draw on the total number of adopters in the population and operate other than at the network level. Hence, we focus on negative word-of-mouth only, and leave the intriguing issue of the negative effects of observations and other forms of negative contagion to future research.

The rest of the paper continues as follows: In the next section, we discuss the effects of negative word-of-mouth at the individual level and its integration into a *dynamic small-world* model. In Section 3, we analyze the adverse economic outcomes of negative word-of-mouth. In Section 4, we explore how a social structure that includes negative word-of-mouth prompts failure, and we offer a model that discriminates between failures and successes. Section 5 presents a structural equations model that enables us to better understand how network structure affects the consequences of negative word-of-mouth. The paper concludes with the managerial implications of the results.

## 2. A growth process in the presence of negative word-of-mouth

### 2.1. Negative word-of-mouth communications

Customers respond to dissatisfaction with a product in a number of ways, including complaints, brand switching, legal action, and negative word-of-mouth. The latter may be particularly harmful, because it requires little effort by consumers, yet it can directly affect the consumption habits of would-be adopters. Worse, it is largely invisible to marketers. One problem in this regard is that only a minority of dissatisfied customers complains to the firm, and so the actual extent of negative word-of-mouth may be greater than what marketers assess it to be (Charlett, Garland, & Marr, 1995).

The individual-level effect of negative word-of-mouth depends on the industry and the specific case. In the fashion industry, Richins (1983) found that most dissatisfied customers talked, on average, to five others. Examining multi-product surveys from Sweden and the US, Anderson (1998) found that highly dissatisfied customers talk to more than ten others. Other numbers have been reported as well (Charlett et al., 1995). While the extent may vary, there is general agreement in the literature that a dissatisfied customer influences others more than a satisfied one (Herr, Kardes, & Kim, 1991; Lacznik, DeCarlo, & Ramaswami, 2001).

This consensus is built both on evidence that dissatisfied customers communicate with others more than satisfied ones (Anderson, 1998; TARP, 1986), and that recipients of this communication place more weight on negative information (Herr et al., 1991). The disproportional influence of unfavorable information is supported by attribution theory (Mizerski, 1982) and, in general, by the fact that such information is more accessible and diagnostic (Herr et al., 1991).

Scant formal analyses are available as to the aggregation of negative word-of-mouth from the individual or network level to the market level, as only recently has agent-based model work

tying individual-level word-of-mouth to aggregate-level response begun to emerge (Goldenberg, Libai, & Muller, 2001). One exception is Moldovan and Goldenberg's (2004) use of Cellular Automata to show how *resistance leaders*, or opinion leaders with negative reactions to a new product, can harm the growth of a new product. The work we present herein does not focus on specific individuals in the market, but rather on the essential mechanisms that tie individual-level negative word-of-mouth to the aggregate financial results of the firm.

## 2.2. Market structure in the presence of negative word-of-mouth

Consider a case in which a new product grows in a given social system. In the presence of negative word-of-mouth, we can think of several pools of market participants, as described in Fig. 1. Note that in any given time period, some consumers can still be potential adopters. They may be still unaware of the new product, or have not received enough information yet to adopt. This pool naturally is larger at the beginning of the process and decreases in size with time.

People who leave the potential adopter stage may move to one of the three pools. Some – labeled *positive adopters* – will adopt the new product and will feel positive about the decision. Hence, they can be expected to influence other potential adopters through future positive word-of-mouth. In the classic diffusion modeling literature, which did not consider negative word-of-mouth, all adopters are positive adopters.

However, in the presence of negative word-of-mouth, some – labeled here *disappointed adopters* – will adopt the new product and will be disappointed. Thus, they have the potential to spread negative word-of-mouth influence on potential adopters. Consequently, a new pool exists, that of *rejecters*. Rejecters are ex-potential adopters who received negative word-of-mouth such that they will not consider the product any longer. This negative word-of-mouth can come from disappointed adopters, as just described, or from other rejecters, who, while they did not buy the product, can still spread negative information to other potential adopters.

The market participant pools described above can serve as a basic approach toward modeling a process that includes negative word-of-mouth. An early study by Midgley (1976) defined a process, including negative word-of-mouth, wherein disappointed consumers influence satisfied adopters with their negative word-of-mouth, transforming them to disappointed as well, instead of influencing potential adopters, as we propose. In a notable

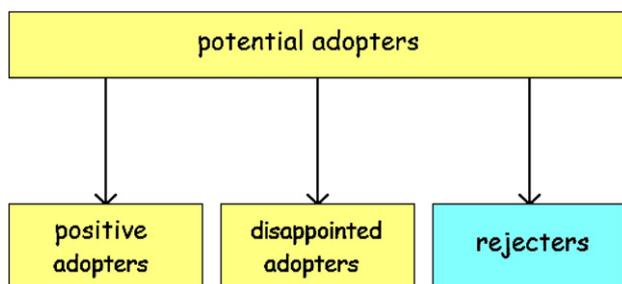


Fig. 1. Pools of market participants.

aggregate-level diffusion model which incorporated negative word-of-mouth in the modeling of the growth process, Mahajan et al. (1984) used a framework similar to what we suggest in this paper. A major limitation of this approach, however, is that it does not consider the dynamics of the social system that drive the growth process, as will be expanded on presently.

Disregard of social network dynamics has long been recognized as one of the primary limitations of aggregate diffusion models (Mahajan & Peterson, 1985), and a major challenge for researchers who want to analyze markets in a parsimonious way, yet must take into account that social structure has a profound effect on information transfer (Barabási, 2003). While there have been efforts to model aggregate diffusion processes in the context of a small number of large segments that interact with each other (e.g., Tanny & Derzko, 1988; Van den Bulte & Joshi, 2007), dynamics related to the communication processes that occur at the individual network level have generally been deemed to be too complex to model at the aggregate level. The inclusion of negative word-of-mouth, which adds further complexity to the modeling of the growth process, presents aggregate modelers with a real challenge. Yet it would be hard to truly understand the role of negative word-of-mouth in the growth process without taking these dynamics into account.

An important issue in this regard relates to the fundamental effect of social network structure on the way agents influence each other. Researchers have been increasingly aware of the need to distinguish between the two kinds of avenues of social influence: *strong ties* and *weak ties* (Brown & Reingen, 1987; Goldenberg, Libai et al., 2001; Granovetter, 1973, 1982; Shi, 2003; Wuyts, Stremersch, Van den Bulte, & Franses, 2004). In typical settings, individuals may interact with their close vicinity. However, the more important interactions with others are not necessarily with individuals' immediate personal network; individuals are also influenced by contacts with others with whom they have tenuous or random relationships. Such influences are labeled "weak ties" to distinguish them from the more stable, frequent, and intimate "strong tie" interactions that characterize individuals' personal networks.

If the importance of weak ties for the transfer of positive information has been acknowledged (Granovetter, 1973) and quantified (Goldenberg, Libai et al., 2001), there has been practically no research on the effect of both weak and strong ties in the presence of both positive and negative information. An interesting question, for example, is whether the "strength of weak ties" remains in effect in the presence of negative word-of-mouth. Our interest in this paper is in gaining an understanding of how the interplay between positive and negative information, as well as weak and strong ties, affects the growth of new products and the consequent economic results, which are of primary managerial interest. To do so, we present our model in the next section.

## 2.3. A model of growth in the presence of negative word-of-mouth

Only a decade ago, Easton and Håkansson (1996) reported that dynamic network research in general ignores the idiosyncratic

relationship between individual consumers in the market. However, in recent years, social science researchers have become interested in the effects of individual- or network-level parameters on market-level factors. In this context, they have increasingly used agent-based models, or complex system methods, in their analyses, with applications to fields such as economics (Rosser, 1999), management (Anderson, 1999), and marketing (Goldenberg, Libai et al., 2001; Krider & Weinberg, 1997; Libai, Muller, & Peres, 2005; Shaikh, Rangaswamy, & Balakrishnan, 2005). These approaches are especially suitable for cases in which a larger number of agents interact in a way that may be simple to model on the individual level, yet too complex to track using simple aggregate approaches. Essentially, researchers build an individual- or network-level model of behavior, and use a simulation to examine how individual-level behavior aggregates to market-level aggregate consequences.

Following this tradition, we start with an individual-level model. We look at a social system composed of potential adopters, i.e., no member has adopted at the beginning of the process. This social system is composed of discrete, smaller social networks. People can communicate with their social network counterparts—these are *strong ties* communications. They can also engage in more random communication with individuals outside their network, i.e., *weak ties*. See Fig. 2 for an extended model of consumer pools that includes both strong and weak ties.

In each period, potential adopters may adopt the product, influenced by either marketing actions such as advertising (parameter  $p$  in the following model), or word-of-mouth that can either follow a strong tie interaction ( $q_s$ ) or a weak tie interaction ( $q_w$ ). Many of these adopters will be satisfied with the product and will supply positive word-of-mouth of their own via either strong- or weak-tie interactions. However, a certain percentage of the buyers e.g.,  $d$ , will be disappointed and spread negative word-of-mouth via both strong and weak ties.

Following the above discussion, we can assume that negative word-of-mouth effect is stronger than positive. Hence, the effect of

negative word-of-mouth may be  $m$  times as strong as that of positive word-of-mouth (for both strong and weak ties). Following negative word-of-mouth, some potential adopters turn into *rejecters*, i.e., those who will not consider the product in the future.

Are rejecters also a source of negative word-of-mouth? It is commonly suggested in the popular business literature that negative word-of-mouth can be passed on by those who did not even purchase the product. However, not much is known on the extent of this phenomenon, or how it changes (weakens) as we move away from the person who actually had the bad experience. It is hard to believe however, that effects are the same for disappointed customers and for people who heard about the product from a far away source. To take into account the difference, our model allows negative word-of-mouth to pass through one layer in an individual's social network. Rejecters affected by a disappointed adopter will not only reject the innovation, but might also spread negative word-of-mouth themselves; third-hand negative word-of-mouth is not considered. This restriction is somewhat conservative regarding negative word-of-mouth's effect.

#### 2.4. Dynamic small world

To examine product growth in the environment described above, we use an agent-based approach that is an extension of the *Small World*, a tool that has received much attention following Milgram's well-known studies about the low degrees of separation between individuals in large social systems (Watts, 1999). Small World was demonstrated as relevant to a variety of social systems through which word-of-mouth information passes on a new product (see Shaikh et al., 2005 and Garber, Goldenberg, Libai, & Muller, 2004 for recent marketing implications).

The original small-world approach described a social system composed of individuals in rather isolated social networks (or "caves") with some communication between caves (Watts, 1999; Watts & Strogatz, 1998). We use a dynamic generalization of the small-world approach that takes into account the existence of various levels of communication. First, as discussed above, we differentiate between the strong ties within the network and the weak ties outside the network. An individual strong-tie connection conveys more reliable information and so has more chance of convincing a potential adopter. Second, while the strong-tie structure inside each social system is fixed, the weak-tie structure is dynamic. In each period, weak ties are randomly reassigned, so that the new structure of the weak-tie network differs from that of the previous period. For example, a study on online groups found that more group interactions and a stronger sense of belonging to the group are related to group identity. While small fixed groups were highly focused on group benefits, large random groups were more focused on individual benefits (Dholakia, Bagozzi, & Pearo, 2004).

The latter assumption reflects the dynamic character of weak ties as described in the original work of Granovetter (1973) and in subsequent literature. The uniqueness of weak ties lies in their randomness from one period to another. In the original

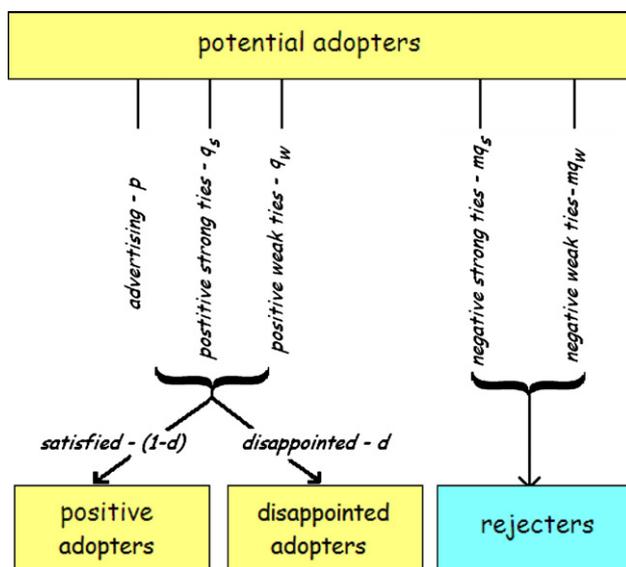


Fig. 2. Pools of market participants: An extended view.

example of Granovetter, weak ties' effect followed a random meeting in a taxi. Because they are more random, and with people with whom the word-of-mouth recipient interacts less, the information may be less convincing as compared with a similar discussion with someone in the strong-tie network. Yet it is the various people meeting from period to period that allows them to be exposed to various kinds of information from other parts of the social system, and hence, causes weak ties to be influential.

Also note that we could have modeled the interactions as fixed, i.e., as if they always exist between some members in various "caves", instead of randomly activated in each period. In a finite period game such as ours, from a practical point of view, the result is exactly the same as ours. What one observes is that an agent has some random contact with members outside his/her own cave. Because the number of periods is limited, it follows that the number of contacts is limited as well, and thus, one cannot distinguish between the two processes. Either an individual has a fixed number of weak contacts, some of which are activated periodically; or s/he has random contacts with the same subgroup.

Hence, we can view this network as composed of time-independent caves with strong ties between them, and vibrating sets of weak ties that each period connect various nodes and therefore (possibly) various caves. Formally, the network can be described as follows:

- 1) *Nodes*: Each cell, representing a potential consumer, can accept one of four states: 1) A value of 0 denotes a potential consumer who has not yet adopted the innovation; 2) a consumer who has adopted the product can either be a satisfied consumer (+1), or 3) a dissatisfied consumer (-1); 4) a consumer affected by a dissatisfied adopter who does not adopt the product, and spreads negative word-of-mouth thereabout, is denoted a *rejecter*, and takes the value of -2. Note that other than 0, the states are absorbing, i.e., once consumers have adopted or rejected the innovation, they remain in their respective states.
- 2) *Links*: The individual maintains relationships with all individuals in his/her network, denoted as *strong ties*, in addition to random ties with individuals outside this network, denoted as *weak ties*. The weak ties are time-dependent and connect various pairs of nodes each period.
- 3) *Dynamics*: The rules that define transitions of potential adopters from state to state are classified into two types: Global factors, such as advertising, where a probability  $p$  exists that an individual will be influenced by these factors to adopt the innovative product; and Local factors, where a probability  $q$  exists that during a given time period, an individual will be influenced by an interaction with another individual (in his/her strong- or weak-tie relationships) who has already adopted the product. In addition, the structure of the network is dynamic in that the weak ties of individuals change randomly each period.

Note that the somewhat more familiar nomenclature would denote the *global* and *local* factors as *external* and *internal*

factors, respectively (Mahajan, Muller, & Wind, 2000). In addition, consistent with the epidemiology literature, we have implicitly assumed that these two forces are independent. This assumption is also consistent with innovation diffusion modeling, beginning with the Bass (1969) model, which has an epidemiology framework as its foundation (see, for example, Mahajan et al., 2000, or the meta-analysis of Sultan, Farley, & Lehmann, 1990).

Note that other approaches could also be taken to model agent-based diffusion. For example, Bell and Song (2005) introduced a utility-based approach with the interactions appearing as thresholds, while ours is a more classic, diffusion-based approach that views the interaction as uncertainty reduction in the form of word-of-mouth. Yet another approach was taken by Shaikh et al. (2005), who modeled a classic small-world model that begins with close neighbors fully connected by strong links, with each link being replaced by some rewiring probability with a weak link to another randomly selected individual. Thus, they can control the connectedness of their network by the rewiring probability that determines the quantity of weak ties that replace strong ties. In our model, we begin as they did, with close neighbors fully connected, and then add (rather than replace) weak ties. We thus control the connectedness by directly varying the quantity of strong and weak ties.

The probability of transition is computed next: Central to an agent-based approach is the construction of the probability of an agent's transition from one state to another, for example moving from potential adopter to positive or negative adopter. For that, we have to first understand the probability of being affected by each kind of information. To do so, we define a number of intermediate measures that will help us to examine these probabilities:

- $S_i(t)$  the cumulative number of adopters at time  $t$  in individual  $i$ 's strong-tie personal networks; of these,  $S_i^{+1}$  are satisfied with the product, and  $S_i^{-1}$  are dissatisfied. We also define  $S_i^{-2}(t)$  as the cumulative number of rejecters at time  $t$  in individual  $i$ 's strong-tie personal networks.
- $W_i(t)$  the cumulative number of adopters at time  $t$  in an individual  $i$ 's weak-tie network; of these,  $W_i^{+1}$  are satisfied with the product and,  $W_i^{-1}$  are dissatisfied. We also define  $W_i^{-2}(t)$  as the cumulative number of rejecters at time  $t$  in individual  $i$ 's weak-tie networks.

Given the above, the probability of individual  $i$  being influenced by either positive word-of-mouth or by advertising at time period  $t$  is given by the following:

$$P_i^{\text{pos}}(t) = 1 - (1 - p)(1 - q_s)^{S_i^{+1}(t)}(1 - q_w)^{W_i^{+1}(t)} \quad (1)$$

Negative word-of-mouth is spread by dissatisfied consumers, and by rejecters, the latter whom were affected by the negative word-of-mouth of the former (and their state commensurately changed from 0 to -2). Thus, the probability

of individual  $i$  being influenced by negative word-of-mouth during time period  $t$  is given by the following:

$$p_i^{\text{neg}}(t) = 1 - (1 - mq_s)^{S_i^{-1}(t)}(1 - mq_w)^{W_i^{-1}(t)} \times (1 - mq_s)^{S_i^{-2}(t)}(1 - mq_w)^{W_i^{-2}(t)} \quad (2)$$

We now turn to the calculation of the transition probabilities. Note that an individual may be exposed to positive information, negative information, both positive and negative, or neither. Thus, the probability of being influenced by only positive word-of-mouth is given by  $(1 - p_i^{\text{neg}})p_i^{\text{pos}}$ , and similarly for only negative word of mouth:  $(1 - p_i^{\text{pos}})p_i^{\text{neg}}$ . Lastly, the probability of being influenced by both positive and negative word of mouth is given by  $p_i^{\text{pos}}p_i^{\text{neg}}$ . We divided the last group so that a proportion of  $\alpha_i$  adopts the product, and  $(1 - \alpha_i)$  rejects, according to their respective size ( $\alpha_i = P_i^{\text{pos}} / (P_i^{\text{pos}} + P_i^{\text{neg}}$ ). The final equations for the probability of individual  $i$  adopting or rejecting, or not being “infected” at time  $t$ , are therefore given by:

$$P_i(\text{adopt}) = (1 - p_i^{\text{neg}})p_i^{\text{pos}} + \alpha_i p_i^{\text{pos}} p_i^{\text{neg}} \quad (3)$$

$$P_i(\text{reject}) = (1 - p_i^{\text{pos}})p_i^{\text{neg}} + (1 - \alpha_i)p_i^{\text{pos}} p_i^{\text{neg}} \quad (4)$$

$$P_i(\text{none}) = (1 - p_i^{\text{pos}})(1 - p_i^{\text{neg}}) \quad (5)$$

Clearly, the three equations add up to 1. Thus, a non-adopter (with a value of 0) has three avenues via which s/he can be affected: with probability  $d \cdot P_i(\text{adopt})$ , s/he adopts and becomes satisfied, receiving the value of +1; with probability  $(1 - d)P_i(\text{adopt})$ , s/he adopts and becomes dissatisfied, receiving the value of -1; with probability  $P_i(\text{reject})$ , after receiving negative word-of-mouth, s/he becomes a rejecter, receiving the value of -2.

### 2.5. Parameter ranges

When basing a decision on parameter ranges, our main focus is to examine ranges that correspond reasonably with market reality. We relied on previous research on the diffusion of innovations and social networks, and the use of agent-based models to create the parameter set for our analysis.

The diffusion parameters ( $p$  and  $q$ ) were chosen to comply with findings on values of aggregate diffusion, transformed to an individual-level grid. The idea is to choose individual-level parameters in a range that will create aggregate diffusion processes of the type actually witnessed in markets. See Sultan et al. (1990), and Jiang, Bass, and Isaacson-Bass (2006) for aggregate diffusion modeling results and standard diffusion parameters; and Goldenberg, Libai et al. (2001) for a discussion of the transformation of parameters to individual-level cellular automata and small world. For example, if one takes the average word-of-mouth parameter of  $q_s$  and  $q_w$  (0.025), and the average strong and weak ties of an individual (36), then the average probability that this person will be affected by internal influence is given by  $(1 - (1 - 0.025)^{36}) = 0.59$ , a number that is comparable

to the internal influence parameter in the growth of durables such as record players or color television sets in the USA (Sultan et al., 1990). These parameters also create diffusion processes compatible in length with the above aggregate findings on USA durables.

Consistent with previous research, the effect of a single weak-tie word-of-mouth interaction ( $q_w$ ) was chosen for a range that is less than that of a single strong-tie conversation ( $q_s$ ). This choice of course does not imply that the aggregate effects behave similarly, as we examine presently.

There is no consensus in the relevant research on what might be a “typical” network size for weak and strong ties. Classic Cellular Automata research typically uses a strong-tie network of eight individuals around each agent. We enable larger networks as well, yet the range covered (8–28) still reflects a reasonable range for a product-related personal network, which is small compared with social system size, and is generally consistent with ranges used in previous similar research (Goldenberg, Libai et al., 2001), and with empirical results (Brown & Reingen, 1987; see also Section 2.6 in this study). Also, network size remains the same for all agents. Note that we are less interested in the absolute value of network size, and more in the effect of a change on that size, as well as the ratio of the sizes of strong-to weak-tie networks, and hence the exact absolute values may matter less here.

Finally, as the percentage of dissatisfied consumers ( $d$ ) and the multiplier  $m$  that describes the relative power of negative word-of-mouth are expected to be highly correlated, we fixed  $m$  at a reasonable level of 2, consistent with accepted industry practice (Hart et al., 1990; TARP, 1986), and changed the parameter  $d$ . However, we ran the basic analysis on various values of this parameter ( $m$ ) with no discernable difference in the results that follow.

We substituted the values of these parameters, performing a total of five runs per parameter (done in order to allow a wide enough variance in the parameter analysis), with the following increments: the sizes of strong ties and weak ties from 8 to 28 in increments of 5; percentage of disappointed consumers in increments of 5%; advertising in increments of 0.00225;  $q_s$  in increments of 0.015; and  $q_w$  in increments of 0.0025.

The range of parameter values is given in Table 1. One issue that should be noted in Table 1 is that of network size. To simplify the following analysis, and since our analysis focuses on the difference between weak- and small-tie effects and not on

Table 1  
Range of parameters used in our analyses

Parameter	Range of values
$r$ — ratio of size of each individual strong-tie personal network divided by size of weak-tie personal networks	0.29–3.5
$d$ — percentage of disappointed adopters	5%–25%
$p$ — global marketing influence parameter (such as advertising)	0.001–0.01
$q_s$ — positive strong-tie word-of-mouth communications parameter	0.01–0.07
$q_w$ — positive weak-tie word-of-mouth communications parameter	0.005–0.015

their absolute network size, we used a “size ratio” variable  $r$ , which is the ratio of the size of each individual strong-tie personal network divided by size of the individual’s weak-tie personal network. Given the network ranges above (the sizes of strong ties and weak ties, varying from 8 to 28), the range of the size ratio is between  $8/28=0.29$  to  $28/8=3.5$ , reflecting cases in which there are more strong ties than weak ties per period, and vice versa.

### 2.6. Empirical support for some assumptions

Rogers (1995) has noted the difficulties of collecting word-of-mouth-related data from consumers as a major obstacle to empirical diffusion-of-innovations research. Indeed, obtaining in-depth data on the spread of positive and negative information over time in a given social system is not trivial, and beyond the scope of this paper. Still, while our assumptions and parameter ranges are generally based on empirical findings in this area, we wished to see if we can find support for some of our basic assumptions that relate to the extent of strong- and weak-tie information upon which consumers might rely. Specifically, we wanted to examine the following two points:

- What is the expected relationship between the sizes of the strong-and weak-tie networks for a given product?
- Are consumers willing to accept second-hand negative word-of-mouth as suggested in our model? Would it change among weak and strong ties?

In order to obtain reasonable ranges, we tested these questions in a  $2 \times 2$  between-subjects setup in which we manipulated the valence of the word-of-mouth (as positive or negative), as well as its source of word-of-mouth (as directly from adopter or second-hand word-of-mouth). For each respondent, we examined the differential response for various strengths of ties (strong or weak). Participants were MBA students, randomly assigned to one of four conditions when they agreed to fill out a questionnaire. As incentive for participation, they were eligible to enter a drawing for an MP3 player. 84 participants answered the questionnaire, of which three outliers who reported over 100 ties were removed from the analysis.

The questionnaire started with questions about the number of strong and weak ties. To estimate the number of strong ties, we asked participants to count the number of people in their address books with whom they have frequent interactions. Then we asked them to estimate the number of people with whom they had randomly met and talked in the past week. This was the estimate of the number of weak ties.

Next, we explained the concepts of strong and weak ties, and gave them a scenario wherein they consult with a friend about a new product that they are considering adopting. Scenarios for various conditions included a positive recommendation from an acquaintance, a disappointed acquaintance, and second-hand information. Respondents were asked about the influence on their decision-making in cases where the source of information is strong and weak tie, respectively.

We used an analysis of variance combining between- and within-subject measures to analyze the above data. In general, the results provide support for the basic assumptions of the literature (and our model) on the effect of word-of-mouth. Respondents reported a stronger effect of word-of-mouth spread by a strong tie than word-of-mouth spread by a weak tie ( $\bar{x}_{\text{strong}} = 5.8$ ,  $\bar{x}_{\text{weak}} = 3.9$ ,  $F=217$ ,  $p<.01$ ), and believed that they would be more affected by negative as compared to positive word-of-mouth ( $\bar{x}_{\text{positive}} = 4.6$ ,  $\bar{x}_{\text{negative}} = 5.1$ ,  $F=7.4$ ,  $p<.01$ ), regardless of the source.

Regarding the number of ties, the results supported our use of roughly equivalent ranges of weak-and strong-tie networks. The mean number of strong ties was 11.9 (the median was 10), and 95% of the answers ranged between 3 and 28. The mean number of weak ties was 13.1 (median 8.5), and 95% of the answers ranged between 1 and 40. We see that the results and specifically the similar magnitudes of the word-of-mouth networks are consistent with the parameter range used in our model. Participants were also more affected by negative word-of-mouth spread by an adopter than by second-hand word-of-mouth ( $\bar{x}_{\text{direct}} = 5.2$ ,  $\bar{x}_{\text{indirect}} = 4.6$ ,  $F=6.7$ ,  $p<.02$ ). However, as can be seen, the difference was not very great. In fact, for strong ties, the numbers were similar, and most of the difference stemmed from weak ties, (for weak ties:  $\bar{x}_{\text{direct}} = 4.3$ ,  $\bar{x}_{\text{indirect}} = 3.5$ ). Given the similarities between the two, we believe that our assumption of a second layer of rejecters that affect others in the same magnitude is reasonable.

### 3. The NPV of bad news

The objective of the first analysis was to study the aggregate response to negative word-of-mouth. We want to compare processes across the range of parameters with and without negative word-of-mouth, as well as examine the economic damage the firm suffers due to negative word-of-mouth. Hence, we first define a one-dimensional measure that will summarize the difference between the processes. Since any change in a growth pattern can have major economic consequences for the industry, we have chosen to express our measure in the ratio of the Net Present Value (NPV) of the growth process between two cases: a process with negative word-of-mouth divided by the same process, yet with an artificial removal of this negative word-of-mouth. Thus, we compute the NPV for the negative word-of-mouth case and for the non-negative word-of-mouth case, using a 10% discount rate per period, which is a reasonable yearly rate for many markets. Their percentage ratio (called the NPV Ratio) will serve as a proxy for the economic difference in the product growth process. For example, if the result of the NPV Ratio is 50% for a certain set of parameters, then the monetary value of the growth process with negative word-of-mouth would be half of a process with the same parameters but without negative word-of-mouth.

Note that the NPV analysis we use assumes that each unit sold supplies one unit of monetary profit based on the revenues and the variable costs of the product. We do not consider losing products, nor the full range of cost allocation to the individual product.

We ran the small-world process described earlier using a C++ application specifically designed for our purpose. Initially, the entire market is unexposed to the product, and thus everyone begins in a zero state. The weak ties are randomly assigned at each period, including the first period. The network contains a fixed number of consumers (3000). We also ran the analysis with a size that is larger by an order of magnitude (30,000), with no significant differences in the result. All combinations were considered in a full factorial design to produce a total of  $5^6 = 15,625$  simulations. We terminated a simulation when the percentage that had made a decision (adopt or reject) reached 95% of the market potential (3000).

In order to understand the role of network and social structure and firm actions, a linear regression was performed with the dependent variable of the NPV Ratio. Table 2 presents the results of the OLS regression, as well as results of the same regression with the addition of one squared parameter to test a hypothesis of a non-linear advertising effect, to be explained presently.

From Table 2, the following results are apparent.

### 3.1. The effects of dissatisfaction

The percentage of dissatisfied buyers ( $d$ ) has the strongest effect on the NPV Ratio, as measured by the standardized coefficient. Since our input was in decimals (e.g., 0.07 sets the fraction of disappointed customers at 7%), this result suggests that, for every percentage point of disappointed customers, our loss due to negative word-of-mouth increases by 1.82%. Note that this number represents the damage caused by negative word-of-mouth only. If we were to calculate a repeat-purchase model in which these customers should cease to re-purchase as well, the damage would be even greater.

### 3.2. The strength of the weak ties

Consider first the Linear Advertising column in Table 2. The first noteworthy result regards the values of the interpersonal parameters  $q_s$  and  $q_w$ . Recall that the dependent variable is the NPV Ratio, and thus an increase in the dependent variable

implies a weaker effect of negative word-of-mouth. The coefficients of both interpersonal parameters are negative, so the higher the parameters, the stronger the effect of negative word-of-mouth on profits.

This result may be surprising, given the popular perception of the generally positive role of weak ties in the spread of information (Brown & Reingen, 1987; Granovetter, 1973). The reasoning for that can be divided into two categories: The first is a micro-explanation that classifies weak ties as more relevant because, after exhausting their strong-tie potential, people actually share the same knowledge with their entire personal network. For example, Granovetter showed that weak ties have a stronger effect on job-hunting because they bring into the consideration set opportunities that did not exist in the set of a specific network. A second explanation is a macro-explanation that shows that, in the case of a large number of small networks, weak ties are responsible for the activation of nets, and they compete well even with advertising (Goldenberg, Libai et al., 2001).

However, in the presence of negative word-of-mouth, in which both strong and weak ties disseminate positive and negative word-of-mouth, weak ties seem to have an especially important role: The standardized regression coefficient of  $q_w$  (weak-tie strength) is about 60% higher than the coefficient of  $q_s$  (strong-tie strength). This difference implies that, indeed, weak ties should not be underestimated, but also for a reason other than the prevailing arguments in the literature: the capacity of weak ties for decreasing the firm's profits in the presence of negative word-of-mouth.

Another way in which the ambiguous power of weak ties is manifested is found in the positive effect of the ratio of strong ties to weak ties on the NPV Ratio. This would imply that if we keep the total number of ties constant, yet increase the number of strong ties, the destructive effects of negative word-of-mouth somewhat dissipate.

### 3.3. The global effect of marketing activity

Unlike interpersonal ties, which spread both positive and negative information, the marketing efforts of the firm ( $p$ ) spread uniformly positive information. One may be tempted to conclude that, in the presence of negative word-of-mouth, the firm will find it optimal to increase advertising in order to combat, and perhaps even eradicate, negative word-of-mouth. However, recall that advertising, while increasing the number of adopters, indirectly also increases the number of disappointed adopters. This increase yields an earlier start—at least partially—of the negative word-of-mouth process. Thus, too much advertising may launch a strong wave of negative word-of-mouth that in time can become yet stronger (due to its logarithmic growth) than in the case of decreased advertising efforts.

In order to test this phenomenon, we added to the regression a squared term of advertising ( $p$ ). The results are presented in the second two columns of Table 2. As can be seen, indeed, the coefficients of  $p$  and  $p^2$  have opposite signs, and the effect of this non-linear behavior is relatively strong. Given the fact that marketing efforts have their own cost, this means that there is an optimum level beyond which the firm is wasting its resources.

Table 2  
Regression results when the dependent variable is the NPV Ratio

Parameter	Linear advertising		Concave advertising	
	Coefficient	Standardized coefficient	Coefficient	Standardized coefficient
$r$ (ratio of strong ties to weak ties)	0.012	0.055	0.012	0.055
$d$ (% disappointed adopters)	-1.822	-0.772	-1.822	-0.772
$p$ (advertising effect)	17.619	0.336	31.943	0.609
$q_s$ (strong-tie word-of-mouth)	-0.7	-0.089	-0.7	-0.089
$q_w$ (weak-tie word-of-mouth)	-6.57	-0.139	-6.57	-0.139
$p$ squared			-1302.17	-0.281
Adjusted $R^2$	73.9%		74.3%	

All coefficients significant at  $p < 0.001$ .

Table 3  
NPV Ratio for various levels of  $d$  (percentage of disappointed adopters) and  $q_s$  (strong-tie word-of-mouth parameter)

	$d$ — low (%)	$d$ — high (%)
$q_s$ — low	77	42
$q_s$ — high	73	30

Instead of fighting negative word-of-mouth, advertising directly decreases the product's market potential.

### 3.4. Interaction effects

In order to examine possible interaction effects among the various parameters, we ran a regression in which interaction terms were added. In this regression, the only two interactions that were close to the main effects in size were  $d$  and  $q_s$ , and  $q_w$  and  $q_s$ . Consider first the interaction between  $d$  and  $q_s$  that is positive (0.15,  $p < 0.001$ ) and can be understood via the example of Table 3.

From Table 3, we can deduce that, as the positive strong-tie word-of-mouth parameter increases, the destructive effect of  $d$ , the percentage of disappointed adopters, increases. The reason is that as  $q_s$  increases, the diffusion of information speeds up, rendering a large percentage of disappointed consumers that is "fatal" to the product. The interaction between  $q_w$  and  $q_s$  is more complex and can be highlighted with the help of the 3D plot presented in Fig. 3.

From the curve pattern in Fig. 3, we can deduce that increasing the level of weak-tie word-of-mouth ( $q_w$ ) decreases the NPV ratio by increasing the power of negative word-of-mouth. When the level of strong-tie word-of-mouth is low, this destructive effect of  $q_w$  is greater (the slope of  $q_w$  is more negative for smaller  $q_s$ ). The reason is that the forces of strong-tie and weak-tie communications are complementary in nature, and thus when  $q_s$  is smaller, the weak-tie communication channel becomes more dominant, causing its destructive power, *ceteris paribus*, to increase.

When the level of weak-tie word-of-mouth communications is high, their ability to spread negative word-of-mouth is strong enough so as to cause the NPV Ratio to decrease, regardless of the effect of strong-tie word-of-mouth. When the weak-tie effect is weaker, the NPV ratio is higher, and negative word-of-mouth has less effect on the market. In this situation, a combination of low weak-tie word-of-mouth and low strong-tie word-of-mouth creates a high NPV, since word-of-mouth is hardly disseminated, and thus information is passed mainly through the positive effect of advertising. As strong-tie word-of-mouth communications increase, NPV ratio decreases, as a result of the propagation of negative word-of-mouth (although positive word-of-mouth is also disseminated, it has a less visible effect, as advertising can reach the same effects as positive word-of-mouth). At a very high level of strong-tie word-of-mouth (and low weak-tie word-of-mouth), NPV Ratio increases again. In this situation, positive strong-tie word-of-mouth starts to show its effect on the NPV by accelerating the diffusion process, overcoming the negative word-of-mouth effect.

## 4. The underpinnings of failures

In the previous section, we analyzed the influence of negative word-of-mouth on the adoption process and profitability. However, negative word-of-mouth is not only responsible for a slowdown of successful processes, but also for transforming a *critical slowdown* of processes into failures that will eventually be removed from the market. Thus, in this section, we sort the effects of negative word-of-mouth into successes and failures. As with success, there are various definitions of failure, in the absence of general agreement over a single representative one (Goldenberg, Lehmann, & Mazursky, 2001). Nevertheless, we adopt one commonly used measure of low sales. A product that, by the end of its diffusion process, was adopted by less than 50% of the target market is defined as a failure. We also use a more stringent definition of a failure: a product that, by the end of the process, was adopted by less than 16% of the market.

The mechanisms of advertising ( $p$ ) and weak-tie word-of-mouth ( $q_w$ ) are rather similar: both forces are responsible for activating nets. If  $p$  and  $q_w$  are very low, nets are not activated, and  $q_s$  cannot be ignited to start working, ergo, the entire process shuts down. However, it is important to distinguish between the two forces. While  $p$  has a purely positive influence,  $q_w$  works in both directions. Thus, in the case of a poor product,  $p$  has an indirect effect (increasing the number of disappointed consumers), but  $q_w$  directly acts to block nets, as well as to launch and magnify the negative word-of-mouth process. The following logistic regression analysis is designed to clarify and quantify these effects, as well as their contribution to product failure.

The same data set that was used in the previous section was classified into two sets: 1) successful processes, with sales above 50% (or 16%) by the end of the process, and 2) failures (below 50% and 16% respectively). A binary logistic regression analysis was performed with a dependent variable (1 = success,

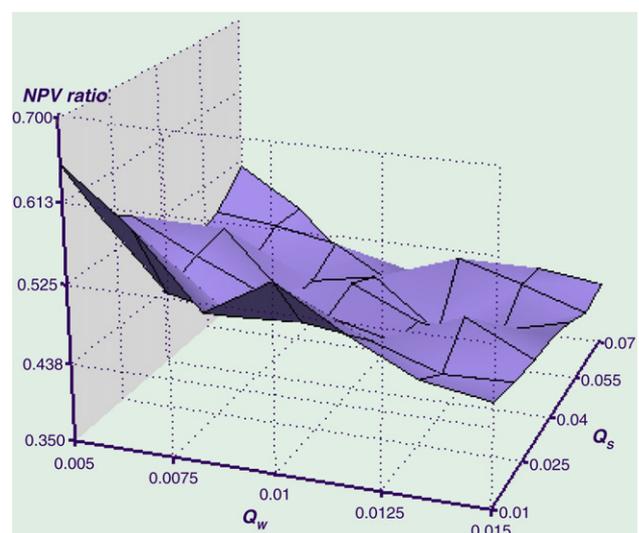


Fig. 3. NPV Ratio for various levels of  $q_w$  (weak-tie word-of-mouth parameter) and  $q_s$  (strong-tie word-of-mouth parameter).

Table 4  
Logit analysis classification table

	Predicted failure (%)	Predicted success (%)
Observed failure	97.0	3.0
Observed success	11.9	88.1

Average correct predictions — 95.1%.

0 = failure) and independent variables that included the same set of variables as in the previous sections.

Table 4 presents the classification results of the model with the 50% criterion as a measure of failure. As can be seen, the logit analysis correctly classifies 95.1% of the cases.

The classification table for the concave advertising case is almost identical to the above table, while that of the 16% criterion is similar but with a slightly lower average correct prediction of 92.1%. Table 5 presents the coefficients of the logit analysis.

Not surprisingly, the parameter that increases the chances of failure most is  $d$ , the percentage of disappointed customers. The strongest positive parameter is the advertising coefficient  $p$ , which increases chances of success. Interestingly, strong- and weak-tie word-of-mouth coefficients affect the chances of failure in opposite directions. Weak ties increase the chances that a product will fail, as they are responsible for activating negative nets. Strong ties, on the other hand (despite the fact that it may not be a smashing success), still support a product's growth.

Some of these differences are even more pronounced if we adopt the 16% figure as a criterion of failure. Recall that with this new criterion, failures are real “duds” (84% of the market potential refuses to adopt it), so the fact that the patterns observed in the previous regression remain in the same signs (except  $p$  squared, to be discussed presently) implies that these results are stable.

Consistent with the previous section, it is interesting to see whether, again, too much advertising (which is the most obvious action a firm is tempted to take) can destroy growth. From Table 5, we see that there is a difference between the success criteria. In the 50% criterion of failure, the non-linear term has a strong effect of  $-0.4$ , implying that too much advertising can push the product to higher monetary losses and failure. In the 16% criterion, however, the non-linear effect of advertising is positive. The reason for this difference lies in the unique relationship of weak ties to advertising. In the 16% criterion, the product has to pass just the 16% cutoff point to be considered a success. Excessive advertising can accomplish this feat because negative word-of-mouth kicks in only later in the process (prompted mainly by the weak ties). This task cannot be accomplished when the product has to pass 50% adoption in order to be considered a success, because by now weak ties have had enough time to shut down networks and fill the market with negative opinions. Thus, in effect, advertising plays a deceptive role. Used excessively, it yields some initial good results, and so a misguided intuition that the product is going to make it, or a deliberate fly-by-night effect (Mahajan et al., 1984). This effect not only dissipates later on but actually plays a destructive role in the growth of a new product in the presence of negative word-of-mouth.

## 5. Underlying structure of negative word-of-mouth: Activations of nets

In the previous sections, we analyzed the effects of the firm's actions and the network structure on the NPV and on product success/failure. However, the precise mechanism of market destruction – i.e., by what means negative word-of-mouth actually destroys growth – still remains to be explored. Although the spread of negative word-of-mouth is mostly invisible in real life, it is easier to trace its effects in a complex model such as the one we used. There are two mechanisms that reflect the spread of negative word-of-mouth. The first is the number of rejecters in the market, and the second is the number of strong-tie networks in which no members have adopted the product. These strong-tie networks that have not begun the adoption process, or *un-activated networks*, not only stall the adoption process. Worse still, they might be exposed to negative word-of-mouth before any member of the network has adopted the innovation, which could infect the network with negative word-of-mouth and block adoption completely. We thus adopt the following terminology:

- 1) Un-activated nets are strong-tie networks in which no member has yet adopted the product, though some may have rejected it. If all members rejected the product and the network will never be activated, we refer to it as a *blocked net*.
- 2) Activated nets are strong-tie networks at least one member of which adopted the product (this member can be either satisfied or disappointed with the product).

The number of rejecters and un-activated nets, if dominant as hypothesized, should strongly mediate between the parameters that we are testing and the NPV of the process. A Structural Equations Modeling can quantify the entire process of rejection formation and its effect on NPV ratio. Therefore, we defined the two mechanisms as two variables that are tested to be mediators. The first is the number of rejecters and the second is the number of un-activated nets, which is a first-order proxy of the slowing down of the net activation process. Both were counted in the middle of the diffusion process, at  $t_{50\%}$ . We also ran it for  $t_{16\%}$  and for  $t_{95\%}$ , and results were similar, except for the direct effect of disappointment rate on the NPV ratio which was insignificant at  $t_{95\%}$ . It seems that, at the end of the process, the effect of disappointed consumers is not by their own effect on NPV

Table 5  
Logit analysis results

Parameter	50% criterion	16% criterion
$r$ (ratio of strong ties to weak ties)	0.3	0.2
$d$ (% of disappointed adopters)	-3.2	-1.4
$p$ (advertising effect)	13.9	17.8
$q_s$ (strong-tie word-of-mouth)	2.7	1.6
$q_w$ (weak-tie word-of-mouth)	-0.2	-0.1
$p$ squared	-0.4	1.1

All coefficients are standardized (Allison, 1999), and are significant at  $p < .001$ .

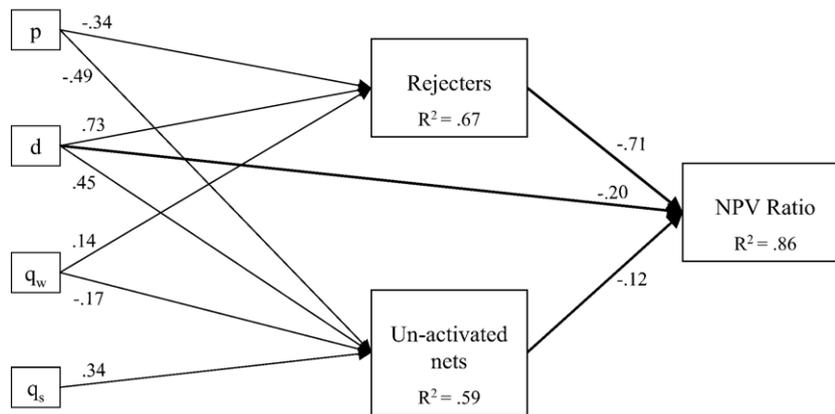


Fig. 4. Structural equations model.

Ratio, but by their effect on others. We will return to this point presently.

The entire data set was tested by structural equations analysis using Amos software. The model is presented in Fig. 4. One parameter, the ratio between the sizes of the individual strong- and weak-tie personal networks, did not show any contribution to the model and was removed for simplicity. Path coefficients and *R*-squared are presented in the model. The structural model produced a  $\chi^2(11, N=15,625)=1083$  ( $p < .001$ ), and a fit of  $NFI=0.98$ ,  $NNFI=0.97$ ,  $CFI=0.98$ , and  $RMSEA=0.08$ .

First, note from Fig. 4 that the number of rejecters and the number of un-activated nets are the two main mechanisms of market destruction, in addition to the percentage of disappointed consumers (as explained, this direct effect also becomes indirect by the end of the process). Surprisingly, when looking at the NPV Ratio, which compares processes with negative word-of-mouth to the same processes without negative word-of-mouth, we see that there are no direct positive effects on the ratio. The only positive effects are through decreasing the number of rejecters (by advertising) or by activating new nets (by advertising or through word-of-mouth).

In addition to the direct effects presented in the above figure, it is interesting to calculate the entire effect of each parameter on NPV Ratio, both by its direct path and through the paths mediated by rejecters and un-activated nets. The total effects are presented in Table 6.

From the previous sections, we learned that weak ties ( $q_w$ ) play an ambiguous role. When promoting both positive and negative word-of-mouth between networks, they activate new networks, yet might completely block them too. Weak ties therefore have two indirect effects on NPV. On the one hand, they increase the number of rejecters, thus decreasing NPV; on the other hand, they activate new nets, thus increasing NPV.

Contrary to weak ties, strong ties ( $q_s$ ) affect only the specific network and have no effect on the infection of new networks with negative word-of-mouth. However, once an un-activated network is affected by negative word-of-mouth (as a result of weak ties), strong ties will infect other members of the network with negative word-of-mouth, and may block adoption completely. They therefore have a strong effect on network blockage. Strong ties do not have any effect on the number of

rejecters, which is a combination of their strong positive word-of-mouth, which will increase the number of adopters before any rejection occurs, with their strong negative word-of-mouth, which in turn will lead to rejection. Thus, when focusing on the destructive effect of negative word-of-mouth, as revealed by the NPV Ratio, strong ties seem to mainly block networks with negative word-of-mouth.

Overall, strong and weak ties promote both positive and negative word-of-mouth concurrently. However, their effect on NPV is quite different. Strong ties do not activate nets, yet they might block them completely once they are infected by negative word-of-mouth. Weak ties can infect new networks with both positive and negative word-of-mouth, and may activate them or block them. Weak ties seem to be the main market mechanism that spreads the positive, but unfortunately also the negative, word-of-mouth, and eventually lead to market destruction.

From Table 6 we can also observe the considerable effect of global advertising ( $p$ ) on NPV Ratio. Advertising competes with word-of-mouth to change the consumers' states. Since advertising encourages adoption, yet not rejection, more advertising will decrease the number of rejecters by increasing the number of adopters before rejection starts spreading. In addition, advertising exposes new networks to the innovation and activates them.

The percentage of disappointed adopters ( $d$ ) has an interesting effect. Disappointed consumers increase the number of rejecters, and, in turn, the number of un-activated nets as a result of these rejecters, yet during the process, disappointment level directly decreases the NPV Ratio. However, as explained above, at the end of the process, the direct effect on NPV Ratio disappears. This result means that the effect of disappointed consumers is not due to their negative word-of-mouth as much as the spread of second-hand word-of-mouth that increases rejection by the end of the process. Companies may therefore

Table 6  
Total effects (paths) of the parameters on NPV Ratio

Parameter	Total standardized effect
$d$ (% disappointed adopters)	-0.77
$p$ (advertising effect)	0.30
$q_s$ (strong-tie word-of-mouth)	-0.04
$q_w$ (weak-tie word-of-mouth)	-0.08

not feel the full impact of their disappointed consumers until the end of the process, by which time the market is completely resistant. In addition, once negative word-of-mouth has started, companies may not be able to stop it by improving the product.

## 6. Discussion

In the course of normal business activity, it is nearly unavoidable that some customers will be dissatisfied, and some will spread negative word-of-mouth. In some cases, firms may even predict that these customers' actions (for example, the level of quality of the product for various customer segments) will cause dissatisfaction among a certain number of customers, yet continue with their desired action, having assessed that the benefits they obtain will outweigh the costs. Our aim here is not to say what the correct course of action is, but rather to point to a way to understand the drivers of the aggregate phenomenon and its possible dynamics, and to quantify the cost structure thereof.

Turning back to our example in the introduction, our results point to the invisible destructive nature of negative word-of-mouth of which managers should beware. Our analysis implied that each additional percentage point of dissatisfied customers increases, by 1.8%, the harm caused by negative word-of-mouth as measured by NPV. This figure was calculated using a conservative approach in which negative word-of-mouth did not spread much beyond the dissatisfied purchaser, and without taking into account the damage of avoided repeat purchases that may become dominant in these product categories. Overall, this study lends quantitative support to the managerial intuition that warns against the considerable losses resulting from customer dissatisfaction (Hart et al., 1990). Using three layers of analysis, we have examined the processes by which negative word-of-mouth affects market evolution. Beyond our findings regarding the destructive power of negative word-of-mouth, two of our findings might seem counterintuitive and thus highlight the importance of an in-depth analysis of negative word-of-mouth.

*The non-linear effect of advertising* — Managers might be tempted to conclude that in the presence of negative word-of-mouth, the firm will find it optimal to increase advertising in order to combat, and perhaps even eradicate, negative word-of-mouth. However, advertising, while increasing the number of adopters, indirectly also increases the number of disappointed customers. This yields an earlier start, at least partially, of the negative word-of-mouth process. Thus, too much advertising may launch an initial push of negative word-of-mouth that in time can gather more momentum (due to its logarithmic growth) than decreased advertising efforts.

*The double-edged sword of weak ties* — Since Granovetter's (1973) seminal work, social science researchers have continued to explore the strength of weak ties that connect various networks and catalyze information assimilation (Brown & Reingen, 1987; Cross & Levin, 2004; Rindfleisch & Moorman, 2001). However, all analyses were conducted under the (extreme) assumption that negative word-of-mouth does not exist. This study is the first to demonstrate the potentially problematic role of weak ties in the presence of negative word-of-mouth. Our analysis shows that weak ties have a consider-

ably stronger effect than do strong ties on the destructive power of negative word-of-mouth, regarding both the NPV Ratio (Table 2), through increasing the number of rejecters (Fig. 4), and the probability of a product's failure (Table 5). Weak ties' power to connect un-activated nets also implies the power to transfer negative information to such nets. Empirical evidence on the double role of weak ties in transferring both negative and positive information in organizational and consumer-related environments is a promising avenue of further research.

### 6.1. The relationship between individual- and aggregate-level models

One might ask about the relationship between the individual-level, agent-based model presented in this paper and the more ubiquitous aggregate diffusion models. Recall that, since an individual can be a strong connector in one group and a weak connector in another, strong-and weak-tie segments cannot be defined in the aggregate models. Thus, consider Fig. 1 and define the following cumulative variables:

$z^+(t) = S^{+1}(t) + W^{+1}(t)$  the number of adopters who adopted and liked the product and disseminate positive word-of-mouth thereabout, in both weak and strong connections.

$z^-(t) = S^{-1}(t) + W^{-1}(t)$  the number of adopters who adopted and were disappointed by the performance of the product and disseminate negative word-of-mouth thereabout.

$R(t) = S^{-2}(t) + W^{-2}(t)$  the number of rejecters who received negative word-of-mouth (both weak and strong), and therefore, will pass on negative word-of-mouth and will not purchase the product.

Let  $p$ ,  $q$ ,  $m$ , and  $d$  be the advertising, word-of-mouth, negative word-of-mouth multiplier, and disappointment parameters, respectively, as defined in Section 2 of the paper. The aggregate equations that follow Fig. 1 are as follows:

$$dz^+/dt = (1 - d)(p + qz^+/N)(N - R - z^+ - z^-) \quad (6)$$

$$dz^-/dt = d(p + qz^+/N)(N - R - z^+ - z^-) \quad (7)$$

$$dR/dt = (mq/N)(R + z^-)(N - R - z^+ - z^-) \quad (8)$$

Given data on a growth pattern of a product, these equations can be tested using standard regression techniques. As an example, we simulated data from our small-world model presented earlier, with a set of parameters as follows:  $p=0.01$ ,  $q_s=0.01$ ,  $q_w=0.005$ ,  $m=2$ , and  $d=0.05$ . The number of strong and weak ties was set to eight. This generated data against which the above three equations could be tested. The result was quite satisfactory with respect to the fit ( $R^2$  of 82%), and the parameter estimation yielded the following interesting observation: the

negative parameters  $m$  and  $d$  were underestimated. The parameter  $m$  that measures the negative word-of-mouth multiplier was estimated to be 1.6 instead of 2, and the disappointment parameter  $d$  came up to be about half its true value (0.023 vs. 0.05). The reason for this underestimation is as follows. Recall that in the agent-based model, the negative word-of-mouth died out quickly, thus second-hand negative word-of-mouth was considered, but not third-hand. In the aggregate model, the negative word-of-mouth keeps on circulating without any decay in its power. Thus, in the aggregate model, the true power of negative word-of-mouth is overstated, and so to compensate, the two parameters that measure its effect are underestimated.

### 6.2. Limitations and conclusions

We see this study as a first step toward a better understanding of how individual-level negative word-of-mouth affects the aggregate. However, it is limited in scope and has a number of other limitations. To allow a parsimonious model, we made many assumptions that can be relaxed in future research. For example, we have modeled negative word-of-mouth as decaying in two steps so that second-hand negative word-of-mouth is modeled, but not third-hand. One possible extension would be to decay negative word-of-mouth in some form such as an exponential decay. Note that this question does not arise in the case of positive word-of-mouth, as the assumption of contagion assures us that the process continues via new adopters. In the case of negative word-of-mouth, this empirical question remains unresolved. In addition, the diffusion literature addresses four major impacts on adoption timing, namely individual differences, innovation attributes, actions of change agents, and network effects. The structure of this paper addresses the latter two impacts, but not the first two. Indeed, the addition of individual differences is possible, yet it comes at the expense of additional parameters and complexity of the model.

We also assumed that, in the close neighborhood of each individual, all individuals are connected and with equal strength. While this is a rather standard assumption in models of this type – especially those using the small-world framework such as Garber et al. (2004) and Shaikh et al. (2005) and also in cellular automata agent-based models such as Goldenberg et al. (2001; Goldenberg, Libai, & Muller 2002) – a more realistic scenario would be one that introduces heterogeneity in networks in this respect. Our ability to generalize on optimal policy following our findings is limited, since the paper does not consider the costs associated with the new product introduction process, nor can it suggest a formal optimal policy. The “value” we refer to in the NPV may take into account variable costs, yet some of the costs, such as advertising, will affect the value of the marketing efforts parameter,  $p$ . Costs of better R&D that will increase the usefulness and innovativeness of the product may affect the level of word-of-mouth and so the value of  $q$ . Any formal optimization that takes into account our results should consider this issue.

From a managerial viewpoint, managers would be well advised to heed the common wisdom that warns of the destructive

power of negative word-of-mouth, as even a small percentage of dissatisfied consumers can cause considerable damage to long-term profits. Unfortunately, the damage of these dissatisfied consumers might persist beyond their network, as they create an invisible diffusion of product rejection which might take a while before it is noticed. Understanding how the presence of dissatisfied customers interacts with the social structure and the ways messages are passed from consumer to consumer is of practical importance. Thus, the optimal level of advertising is highly affected by the process of word-of-mouth and too much advertising might indeed negatively affect profitability. As we showed, the presence of weak ties, which is beneficial to the firm under normal circumstances, might adversely affect it in the presence of dissatisfied consumers.

### 6.3. An afterthought on small-world analysis

Most studies using small-world structures present studies by simulation of the problem at hand. This method, while always subservient to field data in the social sciences, offers some advantages. In particular, it allows for the possibility of repeated simulations to find the mean behavior of stochastic, indeterminate processes, as well as the variation (fluctuations) around the mean behavior. In addition, it enables observing the dependence of the behavior on the characteristics of the network or the adoption process. These characteristics appear in the simulation as the parameters of the model. In particular, it allows for finding the particular form of the dependence, for example of the adoption time on centrality. Such research goals are nearly impossible to obtain from empirical data because a data set that includes the same network with different characteristics (e.g., different number of weak or strong ties) yet the same diffusing process usually does not exist.

As our interest was in understanding the effects of weak and strong ties and their interaction with marketing efforts, we based the structure on the Watts and Strogatz (1998) small-world model. The original model was implemented as a ring of nodes with direct ties between first and second neighbors with some rewired links to create shortcuts. We changed the model so as to allow for the shortcuts to vary in time and related them to social tie strength. In addition, we also have a larger group of strong ties than the traditional small world, and the parameters of the model better reflect real social networks and real-life diffusion processes.

By adding dynamics to the weak ties, increasing sub-networks' sizes, and varying the strength of the ties, we depart from the clean, almost analytical original model. The cost of such departure was the support of the parameter ranges. Although the network, together with two different diffusion processes (positive and negative spread), is much more complex than most small-world models, running times were manageable, and with current computer speed, the extent of complexity of this family of models is not a limitation.

Our extended dynamic small-world model opens an opportunity for examining the economical value of various behavioral (individual-based) information about communication. For example, homophily of ties can be implemented in the

model, and its influence on the aggregate dynamics can be tested (Reingen, Foster, Johnson-Brown, & Seidman, 1984). In fact, any communication-related behavioral finding can be examined in this way. While the findings might consist only of the contribution of the behavior to the aggregate diffusion process, in many cases one can expect to find interactions with other behaviors or network parameters.

There are two significant network types on which dissemination can occur: the scale-free network and the small world. In the first, strong influential nodes with many links exist. The distribution of the number of ties for each node (its degree) follows a power law instead of a uniform distribution as in a pure random network (Barabási & Albert, 1999). This network model is suitable for exploring roles of opinion leaders (hubs). Some may view the two models of small world and scale-free as rival models. Our view is that each model focuses on a different aspect of networks, and together they cover most of the parameters relevant to the marketing context. We believe that, in principle, the same approach can be adopted from opinion leader research by using scale-free networks. Another future research opportunity is to integrate both scale-free and small-world networks to generate one combined simulated network that is even closer to real-life social networks.

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## References

- Allison, P. D. (1999). *Logistic regression using the SAS system: Theory and application*. Cary, NC: SAS Institute, Inc.
- Anderson, E. (1998). Customer satisfaction and word-of-mouth. *Journal of Service Research*, 1(1), 5–17.
- Anderson, P. (1999). Complexity theory and organization science. *Organization Science*, 10(3), 216–232.
- Barabási, A. (2003). *Linked: How everything is connected to everything else and what it means to science and everyday life*, reissue edition. New York: Plume Books.
- Barabási, A., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286, 509–512.
- Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, 15(5), 215–227.
- Bell, D. R., & Song, S. (2005). *Neighborhood effects and trial on the Internet: Evidence from online grocery retailing*. Working paper: The Wharton School.
- Brown, J., & Reingen, P. H. (1987). Social ties and word-of-mouth referral behavior. *Journal of Consumer Research*, 14(3), 350–362.
- Buttle, F. (1998). Word-of-mouth: Understanding and managing referral marketing. *Journal of Strategic Marketing*, 6(3), 241–254.
- Charlett, D., Garland, R., & Marr, N. (1995). How damaging is negative word-of-mouth? *Marketing Bulletin*, 6, 42–50.
- Cross, R., & Levin, D. Z. (2004). The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management Science*, 50(11), 1477–1490.
- Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International Journal of Research in Marketing*, 21(3), 241–263.
- Easton, G., & Håkansson, H. (1996). Markets as networks: Editorial introduction. *International Journal of Research in Marketing*, 13(5), 407–413.
- Garber, T., Goldenberg, J., Libai, B., & Muller, E. (2004). From density to destiny: Using spatial dimension of sales data for early prediction of new product success. *Marketing Science*, 23, 419–429.
- Goldenberg, J., Lehmann, D. R., & Mazursky, D. (2001). The idea itself and the circumstances of its emergence as predictors of new product success. *Management Science*, 47, 69–84.
- Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: A complex system look at the underlying process of word-of-mouth. *Marketing Letters*, 12, 209–221.
- Goldenberg, J., Libai, B., & Muller, E. (2002). Riding the saddle: How cross-market communications can create a major slump in sales. *Journal of Marketing*, 66(2), 1–16.
- Granovetter, M. S. (1973, May). The strength of weak ties. *American Journal of Sociology*, 78, 1360–1380.
- Granovetter, M. S. (1982). The strength of weak ties: A network theory revisited. In P. V. Marsden & Nan Lin (Eds.), *Social structure and network analysis* (pp. 201–233). Thousand Oaks, CA: Sage Publications.
- Hart, C., Heskett, J. L., & Sasser, E. W. (1990). The profitable art of service recovery. *Harvard Business Review*, 68(4), 148–156.
- Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research*, 17(4), 454–462.
- Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Readings, MA: Addison-Wesley.
- Jiang, Z., Bass, F. M., & Isaacson-Bass, P. (2006). Virtual bass model and the left-hand data-truncation bias in diffusion of innovation studies. *International Journal of Research in Marketing*, 23(1), 93–106.
- Joshi, Y., Reibstein, D., & Zhang, J. Z. (2006). *Optimal entry timing in markets with social influence*. Working paper: The Wharton School.
- Krider, R. E., & Weinberg, C. B. (1997). Spatial competition and bounded rationality: Retailing at the edge of chaos. *Geographical Analysis*, 29, 16–63.
- Laczniak, R. N., DeCarlo, T. E., & Ramaswami, S. N. (2001). Consumers' responses to negative word-of-mouth communication: An attribution theory perspective. *Journal of Consumer Psychology*, 11(1), 57–73.
- Libai, B., Muller, E., & Peres, R. (2005). The role of seeding in multi-market entry. *International Journal of Research in Marketing*, 22(4), 375–393.
- Mahajan, V., Muller, E., & Kerin, R. A. (1984). Introduction strategy for new products with positive and negative word-of-mouth. *Management Science*, 30(12), 1389–1404.
- Mahajan, V., Muller, E., & Wind, Y. (2000). *New-product diffusion models*. Boston, MA: Kluwer Academic Publishing.
- Mahajan, V., & Peterson, R. A. (1985). *Models for innovation diffusion*. Thousand Oaks, CA: Sage Publications.
- Midgley, D. F. (1976). A simple mathematical theory of innovative behavior. *Journal of Consumer Research*, 3(1), 31–41.
- Mizerski, R. W. (1982). An attribution explanation of the disproportionate influence of unfavorable information. *Journal of Consumer Research*, 9(3), 301–310.
- Moldovan, S., & Goldenberg, J. (2004). Cellular automata modeling of resistance to innovations: Effects and solutions. *Technological Forecasting & Social Change*, 71(5), 425–442.
- Reingen, P. H., Foster, B. L., Johnson-Brown, J., & Seidman, S. B. (1984). Brand congruence in interpersonal relations: A social network analysis. *Journal of Consumer Research*, 11(3), 771–784.
- Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of Marketing*, 47(1), 68–78.
- Rindfleisch, A., & Moorman, C. (2001). The acquisition and utilization of information in new product alliances: A strength-of-ties perspective. *Journal of Marketing*, 65(2), 1–18.
- Ritson, M. (2003, March). Prepare for a virtual battering if you fail to deal with complaints. *Marketing*, 13, 16.
- Rogers, E. M. (1995). *Diffusion of innovations*. New York: Free Press.

- Rosser, B. (1999). On the complexities of complex economic dynamics. *Journal of Economic Perspectives*, 13(4), 169–192.
- Shaikh, N. I., Rangaswamy, A., & Balakrishnan, A. (2005). *Modeling the diffusion of innovations through small-world networks*. Working paper: Penn State.
- Shi, M. (2003). Social network-based discriminatory pricing strategy. *Marketing Letters*, 14(4), 239–256.
- Sultan, F., Farley, J. H., & Lehmann, D. R. (1990). A meta-analysis of applications of diffusion models. *Journal of Marketing Research*, 27(1), 70–77.
- Tanny, S., & Derzko, N. A. (1988). Innovators and imitators in innovation diffusion modeling. *Journal of Forecasting*, 7(4), 225–234.
- TARP — Technical Assistance Research Programmes (1986). *Consumer complaint handling in America: An update study*. Washington, DC: White House Office of Consumer Affairs.
- Van den Bulte, C., & Joshi, Y. (2007). New product diffusion with influentials and imitators. *Marketing Science*, 26(3), 400–424.
- Van den Bulte, C., & Stremersch, S. (2004). Social contagion and income heterogeneity in new product diffusion: A meta-analytic test. *Marketing Science*, 23(4), 530–544.
- Ward, J. C., & Ostrom, A. L. (2006). Complaining to the masses: The role of protest framing in customer-created complaint Web sites. *Journal of Consumer Research*, 33(2), 220–230.
- Watts, D. J. (1999). Networks, dynamics, and the small-world phenomenon. *American Journal of Sociology*, 105(2), 493–527.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature*, 4(393), 440–442.
- Wuyts, S., Stremersch, S., Van den Bulte, C., & Franses, P. H. (2004). Vertical marketing systems for complex products: A triadic perspective. *Journal of Marketing Research*, 41(4), 479–487.