The Quicker One is the Better One? – How to Fight Negative Word of Mouth

Completed Research Paper

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Abstract

With the rising popularity of online social networks it became much easier for firms to spread viral messages for marketing purposes. But on the reverse side, negative messages can also spread much more easily and may harm the reputation of a firm severely. Therefore, we investigate how firms can react on negative word of mouth in online social networks with the help of positive word of mouth. For this, we develop a novel diffusion model that incorporates several new aspects: the aging of a message, the content of a message, the change of opinion, the delay between the negative message and the firm's reaction, and different kinds of markets. Results show that a firm is better off when reacting with a carefully designed message even if it takes some time instead of reacting quickly or with multiple seeds but with a message of lower quality.

Keywords: Information diffusion, online firestorms, social networks, word of mouth

Introduction

The fast evolution of online social networks (OSN) such as Facebook or Twitter poses new challenges to marketing and customer relationship management (Henning-Thurau et al. 2010). On the one hand, users disclose much information of their personality and about their communication network (Katona et al. 2011) that can be used to improve marketing measures, on the other hand negative word of mouth (NWOM) can spread easily through OSN badly damaging a firm's reputation (Van Laer and De Ruyter 2010). Therefore, much research was done during the past years examining what makes messages go viral (Berger and Milkman 2012; Chiu et al. 2014; Eckler and Bolls 2011), how this affects a firm's economic success (Vázques-Casielles et al. 2013), or how to measure the success of a viral marketing campaign (Ewing et al. 2014). Indeed, the idea of viral marketing is very promising as it has become much more efficient and quicker in the Internet era than before (Probst et al. 2013). Nowadays, it is possible to reach a huge number of (potential) customers with such campaigns faster and with less expenditure than it was in offline-only social networks (Dobele et al.2005; Berger and Milkman 2012). Messages can easily be spread to thousands of network participants and are passed by them to other participants in a short period of time (Mangold and Faulds 2009). Therefore, several papers have investigated the question of how to reach a maximum number of people in a network with a limited budget for the initial seeding (e.g. Chen et al. 2010a/b; Goyal et al. 2011; Kempe et al. 2003; Wang et al. 2010). But this fast and low cost method of communication bears several severe risks. Once a firm has launched a message, it has already lost control over it and its ways of communication. An ill-conceived campaign or a mistreated customer can provoke NWOM that might strongly harm a brand and cause customer losses (Henning-Thurau et al. 2010) because people can spread the initial message over OSN (viral marketing) as well as a changed message with a different and unintended tenor (Illia 2002). Such unintended messages usually express the dissatisfaction of customers with a firm in a harsh manner and often without substantial criticism (Pfeffer et al. 2014). Because negative messages are perceived to be more credible than positive ones (Rozin and Royzman 2001), they can spread very fast resulting in so-called online firestorms (Mochalova and Nanopoulos 2014). In this respect, it is crucial to react in the right manner (Van Noort and Willemsen 2011) and with little delay. Otherwise, it might not be possible to counteract and curtail the firestorm efficiently (Mochalova and Nanopoulos 2014). Therefore, it is important for firms to permanently monitor OSN so that NWOM is detected in an early stage and to develop strategies on how to react on NWOM (Roehm and Tybout 2006; Stauss 2000).

The way how to react on NWOM is not obvious (Pfeffer et al. 2014). When facing a unilateral risk like NWOM, one has to trade the costs of the risk off against the costs of avoiding the risk. In the case of NWOM that means that a firm must weigh the loss of reputation that NWOM may cause and set it off against the measures that can be taken to reply to NWOM. Even if it is quite expensive, it can be much cheaper to satisfy an unjustified complaint of a customer than to counter the NWOM that this customer may spread in OSN (Killian and McManus 2015). Otherwise, although NWOM can grow and result in an online firestorm, it can be better just to observe the communication and do nothing instead of starting a countermeasure. Usually, the reach of a single message is low and its spread is slow (Cha et al. 2009) because people are exposed to a huge amount of information in OSN (Canali and Lancelotti 2012). Therefore, messages are aging quickly and because people pay less attention to older messages, they tend to spread less probably than newer ones (Falkinger 2007). However, NWOM threatens a firm's reputation so that OSN must be monitored (Malthouse 2007). After a message reached a certain spread, it can be difficult and very costly to fight against NWOM (Pfeffer et al. 2014) even if it is unjustified. Thus, if a message appears to become severely threatening, one should take countermeasures against its further spread. A typical measure is to initiate a positive word of mouth (PWOM) campaign that lessens or restricts the NWOM spread (e.g. Mochalova and Nanopoulos 2014; Nguyen et al. 2012).

Several papers (see next section) studied this situation and investigated the question which network participants should be chosen as initial seeds for the PWOM campaign. These papers inherently assume that network participants can be activated by marketing activities with a relatively high probability. In reality, this assumption may not necessarily hold. In fact, firms or marketing agencies do not only rely on activating more or less unknown network participants but cultivate good relationships to a rather fixed number of participants whose number is quite small in comparison to the network size but who can be activated immediately. Therefore, the selection of new seeds in networks plays a less important role in case of an upcoming online firestorm. Instead, it is crucial to analyse which kinds of messages evoke firestorms and how they can be countered in order to prevent firestorms (Henning-Thurau et al. 2010). Although the marketing literature already investigated characteristics of messages that make them go viral and showed that emotional aspects and content are important factors for viral marketing (e.g. Botha and Reynecke 2013; Chiu et al. 2014; Eckler and Bolls 2011; Radighieri and Mulder 2012; Van Laer and De Ruyter 2010), none of the existing papers that analyse the concurrent spread of NWOM and PWOM in one network considers the characteristics of a message, namely its argument quality (AQ) and its expressiveness (EX) (Allsop et al. 2007; Sweeney et al. 2010).

In this paper, we contribute to the existing literature in the following ways: First, we consider the two parts of a message and analyse how firms should react on NWOM with different levels of EX and AQ. Van Laer and De Ruyter (2010) have shown that the form of a response (narrative versus analytical) plays an important role when answering to NWOM. Hence, it is crucial to know for firms when and how to react on different levels of EX and AQ. Secondly, we include aging of messages in our model. Aging is usually neglected in the related literature of concurrent message spread but models the spread of messages in a network in a more realistic way. People communicate and forward messages to shape their reputation in their network (Lampel and Bhalla 2007). With increasing age it is more likely that network peers already know about the message. But if already known messages are spread, the reputation decreases. Therefore, people forward older messages less likely than new ones in order to not harm their own reputation. In addition, people are exposed to a plethora of news (Canali and Lancelotti 2012). That means that messages continuously sink in the message list and can easily be forgotten after a while (Falkinger 2007).

Thirdly, we consider a delay between the occurrence of NWOM and a firm's reaction on it. Usually, NWOM can spread for a period of time without being noticed by the firm. Only after a while, if a certain threshold is exceeded, monitoring tools raise an alarm so that countermeasures can be taken. Although this assumption is more realistic than reacting on NWOM immediately, only a few papers (e.g. Mochalova and Nanopoulos 2014; Nguyen et al. 2012) consider such a delay. Fourthly, the "infection" of network participants is not fixed but can be altered. A person who already believes a message can be convinced of the opposite as long as s/he receives new information in form of messages from network neighbours. That means that (1) a person's opinion state can swing between the negative and the positive message and therefore (2) a person is not "saved" if PWOM reaches her/him before NWOM. This opinion switching is only considered in very few papers (Trpevski et al. 2010; Irfan and Ortiz 2011) that are limited to the observation of message spread but without further economic interpretations and insights. Finally, we distinguish different kind of markets. The belief in a message depends not only on the message itself but also on the kind of product that is affected by the message (Batra et al. 2001). In the fashion market for example, people are much more influenced by their peers than in the food market (Delre et al. 2007a). Because of this, we use a market parameter with which such differences can be considered.

The remainder of this paper is organised as follows. The next section gives an overview of the related literature in the field of (competitive) information spread in OSN. The third section develops a diffusion model that incorporates the above-mentioned aspects and therefore extends the existing diffusion models. This model is more complex than the popular usually used diffusion models. Therefore, it is analysed numerically in the fourth section instead of analytically. The paper concludes with managerial implications and a summary.

Literature Review

Domingos and Richardson (2001) were the first who recognised the importance of the network structure for viral marketing instead of focusing solely on customers' characteristics. They formulated the problem of influence maximisation for a given network to choose a set of network participants called seeds for a marketing message so that the message achieves a highest as possible spread in the network. Kempe et al. (2003) and Kempe et al. (2005) acted on that problem suggestion and formulated it as a discrete optimisation problem. They used two different diffusion models, the independent cascade model (ICM) and the linear threshold model (LTM), and showed that the influence maximisation problem is NP-hard but submodular. Being submodular means that the problem although NP-hard can be approximated with the help of a hill climbing algorithm in acceptable time (Nemhauser et al. 1978). Because the hill climbing algorithm proposed by Kempe et al. is not efficient, several authors investigated efficient algorithms that scale with increasing networks (e.g. Chen 2009; Chen et al. 2009; Chen et al. 2010a; Chen et al. 2010b; Leskovec et al. 2007; Wang et al. 2010 to name only a few). All these paper have in common that they focus on one message whose spread is intended to be maximised within the network. This problem is motivated from marketing where a marketing campaign with limited budget shall address and reach a maximum of people.

The problem that we are focusing on in this paper concerns the spread of at least two messages that compete for the network participants' conviction. A participant can either be convinced by none or by one message but not by two messages at the same time. The papers in this field can be divided into two groups. The first group in general assumes two competing firms each with the aim to maximise its influence in the network. One firm is the first (she in the following) and the other firm is the second mover (he). The steps of the first mover are known to the second mover. The second mover tries to maximise his influence in the network by choosing network participants as seeds for his marketing campaign. Papers of this group can be found in Table 1 with the objective "influence maximisation". Results show that being the first mover is not advantageous and that the second mover can outperform her even with a limited budget (Carnes et al. 2007; Kostka et al. 2008). If the first mover has chosen her seeds, the second mover will tend to choose his seeds nearby (Goyal and Kearns 2012). As a consequence, it seems to be better to compete in several smaller markets in order to reach together a high total spread of a technology than trying to influence the whole network from the beginning. However, networks seem to support only a certain number of concurrent messages (or products). If this number is exceeded, some messages will die out (Pathak et al. 2010). Borodin et al. (2010) as well as Chen et al. (2011) (the latter being a representative of the following second group) have shown that already small changes to the general competitive diffusion models destruct the submodularity property which implies that the optimal solution for influence maximisation can hardly be approximated.

Author	Objective	Diffusion Model	Messages	Switching	Delay	Findings
Bharathi et al. (2007)	influence maximisation	independent cascade model	equal	–	delayed infection	first as well as second mover can efficiently find an optimal set of seeds; the costs for competition are at most a factor of 2
Borodin et al. (2010)	influence maximisation	different adapted linear threshold models	equal	–	–	adapted models are NP-hard and not submodular, optimal solution can hardly be approximated
Budak et al. (2011)	influence blocking maxi-misation when information about network is missing	independent cascade model with positive domination	dominant	–	delay	simple graph heuristics perform similarly to greedy heuristics in the full information case; proposed algorithm allows 90% missing data before performance declines
Carnes et al. (2007)	influence maximisation	distance based model wave propagation model	equal	–	delay	second mover can outperform first mover with a limited budget
Chen et al. (2011)	influence maximisation; analysing the influence of/ sensitivity to product quality	independent cascade model extended by quality	dominant	–	–	universally good quality does not exist for optimal spread; model extensions destruct submodularity
Goyal and Kearns (2012)	influence maximisation (game theoretic framework)	adapted linear threshold model	equal	–	–	competitors are better off starting to compete in nearby instead of distant nodes
He et al. (2012)	influence blocking maximisation	competitive linear threshold model with negative domination	dominant	–	–	given problem is submodular algorithm outperforms simple graph heuristics
Irfan and Ortiz (2011)	influence maximisation	game theoretic approach	non-competitive	adoption and rejection	–	no managerial insights, algorithm provided to find the most influential nodes
Kostka et al. (2008)	influence maximisation	simple propagation model (without personal influence)	equal	–	delay	first mover is not always advantageous, second mover can outperform first mover
Mochalova and Nano-poulos (2014)	influence blocking maximisation	independent cascade model with negativity bias	dominant preferences	–	delay	seeds can prevent about the tenfold of their number from adopting a message; the earlier the counter strategy starts the more people are saved
Nguyen et al. (2012)	influence blocking to a given percentage	independent cascade model and linear threshold model with positive domination	dominant	–	delay	blocking misinformation to a certain percentage with a minimum number of nodes is NP-hard and can hardly be approximated
Pathak et al. (2010)	influence maximisation	generalised linear threshold model	equal	–	–	number of surviving messages is independent of the number of competing messages
Trpevski et al. (2010)	analysis of competitive message spread	susceptible-infective-susceptible model	dominant preferences	conversion to not-infected due to oblivion	–	for non-dominant messages it is difficult to survive but possible; message spread has to exceed a threshold independent of network and starting point in order to survive

Table 1. Related literature of word of mouth in a competitive environment

While the papers of the first group treat the two spreading messages as being equal, the second group assumes one message to dominate the other. This can be observed when comparing NWOM and PWOM. Usually, the former is said to be stronger (Anderson 1998; Bone 1995) and to spread twice more likely than PWOM (Heskett et al. 1997). In this context, papers of the second group investigate how NWOM can be stopped or restricted. Instead of maximising the influence of PWOM, the intention is to block the NWOM and to save as many network participants from being infected by NWOM as possible. This problem is called "influence blocking maximisation". In Budak et al. (2011) and Nguyen et al. (2012) a wrong message spreads through the network. Now, the main purpose is to stop this message and to minimise its influence in the network. This is done by clarifying the facts and sending a message that contains the truth to selected network participants. Both papers assume that the positive message is stronger than the negative message because people can distinguish between a lie and the truth and will always believe the truth. This indeed may hold for rumours like the wrong announcement of President Obama's death in July 2011 (Nguyen et al. 2012) but not in the case of justifiable bad experiences or reported opinions like "worst smartphone ever". Hence, in general, the situation is not clear. Often, negative rumours arise e.g. about the quality of a product harming a brand's reputation. Irrespective if such rumours are true or false, the truth can hardly be verified, is not unequivocal, or lies in the eye of the beholder. In this case, because of the negativity bias (Rozin and Royzman 2001) people tend to believe and forward negative messages more often than positive ones. Trpevski et al. (2010) analysed this setting of a dominant and a non-dominant message when network participants can switch from not believing a message to believing and back to not believing. They found that for the non-dominant message it is often difficult even to survive. However, in order to survive, messages have to exceed a certain threshold depending on the network but independent of the starting point of both messages. This poses the problem of how to fight NWOM in OSN efficiently. He et al. (2012) and Mochalova and Nanopoulos (2014) address this problem and develop different strategies on how to select seeds in a network in order to minimise the influence of NWOM. Both papers use localised properties of the network for choosing seeds and outperform the greedy algorithm that Kempe et al. (2003) originally introduced for the influence maximisation problem.

This paper is mostly related to the papers of He et al. (2012) and Mochalova and Nanopoulos (2014) who aim to fight NWOM instead of maximising the influence of PWOM. However, it differs to the existing approaches in several ways. While all of the above approaches aim for finding an efficient algorithm to choose an optimal set of seeds, we focus on the characteristics of the messages as well as on the number of seeds used for the counter measure. Doing so, we assume that the set of seeds cannot be chosen but is already given to fight NWOM. This seems to be more realistic because of several reasons: First of all, it is doubtful if a firm can really activate those seeds chosen by algorithms in case of an online firestorm. It is reasonable that the selected network participants can only be activated with a certain likelihood. This is usually neglected in the aforementioned papers. Secondly, firms typically try to place potential seeds into a network in advance so that they can gain reputation and build relationships to other network participants. Or they try to find existing network participants who agree to work together with the firm. That means that in case of an emergency these network participants are activated to spread the desired PWOM against the NWOM spread instead of searching for new potential PWOM seeds. This also enables firms to react to NWOM more quickly. Thirdly, activating only preselected seeds ensures that the desired PWOM message will not be modified before it is forwarded in the network. If the firm uses algorithms to select influential nodes of the network, this cannot be guaranteed. Instead, it is quite reasonable that the selected seeds may modify the message before sending (Illia 2002). Therefore, we assume that a firm has preselected seeds in the network with whom NWOM will be fought. Even if firms try to work together with influential nodes of the network, this selection of seeds resembles more a random choice that will be less effective than using seed selection algorithms (He et al. 2011).

Another difference lies in the possible opinion change. Except for Trpevski et al. (2010) who allow to forget a message and Irfan and Ortiz (2011) who analyse a non-competitive setting all the other papers consider a so-called progressive spread (Kempe et al. 2003) where a network participant does not change opinion once s/he is convinced of NWOM or PWOM. In contrast to this, we lift this restriction. As long as a network participant gets new messages from neighbours s/he can change her/his mind and switch to the other opinion. This opinion change depicts the problem in a more realistic way because first of all people tend to comply with their peers and if they encounter that more and more of their peers adopt a message they will also do so. Secondly even if there might be a certain inertia, people think about new information that they get and will adopt a new opinion if the information is convincing enough. As in Mochalova and Nanopoulos (2014), we also consider a time delay between the initial NWOM message and the reacting PWOM message because usually, firms cannot react immediately on NOWM. Typically, the NWOM message spreads for a certain period of time and will be recognised by the firm when a certain number of people have forwarded the message already. In addition, depending on its level of expressiveness and arguments' quality, a message spreads more or less. Therefore, we also consider in contrast to the aforementioned papers, that messages are not only just positive or negative but have an emotional and a rational dimension that characterise its content (Allsop et al. 2007; Sweeney et al. 2010).

Model

General Model

When studying the diffusion of word of mouth, usually the ICM or the LTM are considered (see table 1). Both models are based on an undirected network G=(V,E) with V being a set of nodes or network participants and E being the edges between the nodes, representing the relationship between the network participants (see Kempe et al. 2003 for the following explanations). Nodes who believe the message are called infected. In the LTM, each edge $(i,j)\in E$ is associated with a weight $b_{ij}\in[0,1]$ that can be interpreted as the intenseness of the relationship between the nodes i and j. The sum of weights of all neighbours of i shall not exceed the value of 1. This implies that in general $b_{ij}\neq b_{ji}$.

$$\sum_{j,(i,j)\in E} b_{ij} \leq 1, \qquad b_{ij} \in [0,1] \tag{1}$$

Then, a message spreads in the network G as follows: A node either believes the message and is therefore infected or not. Let INF_t be the set of infected nodes in time step t. Each time step t, an uninfected node $i\notin INF_t$ has a look at its neighbours j. If the sum of weights of all infected neighbours $j\in INF_t$ exceeds an individual threshold $\Phi_i\in[0,1]$ of i, then i switches from not infected to infected:

$$INF_{t+1} = INF_t \cup \left\{ i \,\middle|\, i \in V : \sum_{j,(i,j)\in E \wedge j\in INF_t} b_{ij} \geq \Phi_i \right\}, \qquad \Phi_i \in [0,1] \tag{2}$$

The LTM considers so-called peer-group pressure. If the pressure coming from friends is high enough, a person adopts the opinion of the group. In contrast, the ICM focuses more on the individual personal relationship between people. Here, the message spread depends on a global probability p_{ij}. Each time step t, a node i that switched from uninfected to infected in step t-1, tries to infect its uninfected neighbours j, $(i,j)\in E$. i succeeds in infecting j with probability p_{ij}. If i does not succeed in infecting j at step t, there will be no other try in later time steps t'>t. In Kempe et al. (2003), p_{ij} is assumed to be a system parameter. But is also conceivable, that p_{ij} is an individual parameter between i and j representing the intenseness of their personal relationship. Thus, the LTM completely relies on the social pressure that a person faces while the ICM solely uses the personal relationship between two network participants even though the probability of infection increases the more messages one receives. In addition, both models neglect the content of the message itself. Each message is treated the same, no matter if it is convincing or not.

Usually, the ICM and LTM are adapted to the competitive case. In this paper, we orientate to concepts of both models. But due to the above-mentioned limitations, we develop a diffusion model that tries to overcome these disadvantages. Our model resembles in several ways the concept of a neuron of a neural network (Lackes and Mack 2000) with influencing neighbours being the dendrites, an input function being the soma and an output function being the axon and trying to influence other neighbours. The general concept is as follows: We regard an undirected network G=(V,E,B) with V being the nodes that represent the network participants, E being the edges that represent the relations between the nodes, and B being a function that assigns a weight b_{ij} to the edges $(i,j)\in E$: $B: E\rightarrow[0,1]$, $(i,j)\mapsto b_{ij}$. We call b_{ij} the intenseness of the relationship between i and j. While Kempe et al. (2003) postulate that the sum of weights b_{ij} leading to a node i shall sum up to a maximum of 1, we just assume that $b_{ij}\in[0,1]$. Values of b_{ij} closer to 1 indicate a strong-tie relationship between node i and j, whereas values close to 0 represent a weak-tie relationship. The advantage is that within the whole network the b-values are comparable between different neighbourhoods. In the network, two messages with opposite valences can spread: an NWOM and a PWOM message. In time step t, network participant i (he) receives a message from his neighbour j (she) to whom he is tied with a degree b_{ij}. This message can either be NWOM or PWOM. After receiving all messages, he decides whether to believe this message or not depending on the characteristics of the message and his neighbours who have sent the message to him. Then he decides if he forwards the message in time step t+1 to other neighbours to whom he has not sent the message in past steps. The decision of forwarding the message depends on the credibility of the message, the relationship to his particular neighbour and the age of the message. If the network participant receives both the NWOM and the PWOM message, he has to decide in each step which of the received messages he wants to believe. He may only forward that message of which he is convinced. Only in case of being neutral it is possible that he forwards both messages.

Credibility of a Message

According to Deutsch and Gerard (1955), the credibility of a message depends on two factors: normative social influence (NSI) and informational social influence (ISI). NSI describes people's wish to comply with the expectation of others in order to be not socially excluded. In the LTM, this effect is represented by the individual threshold Φ_i . If this threshold is low, the person has a strong wish to comply with others. If the threshold is high, we are facing a person with a strong personality. In contrast, ISI refers to people's tendency to accept received information as a proof of facts. While NSI is independent of the content of a message and represents the social pressure that changes over time, ISI concerns the time independent content of a received message. If the content is weak, a person tends to mistrust the message and vice versa.

Which factor influences the credibility of a message more, depends on the market that is analysed (Batra et al. 2001). Concerning fashion for example, the social influence is much greater than concerning food (Delre et al. 2007a). That means in fashion markets, people pay much more attention to the opinion of others than in food markets. We call markets where the opinion of others is more important collectivistic markets and those markets where the content of the message is in the foreground of a decision individualistic markets. However, the weighting between ISI and NSI does not depend only on the market but may vary on the individual level from person to person (Chu 2009; Delre et al. 2007b; van Eck et al. 2011) according to expertise (Chu 2009; De Bruyn and Lilien 2008; Fan and Miao 2012), opinion (Qiu et al. 2012; Mochalova and Nanopoulos 2014), and preferences (Lord et al. 2001; Fan and Miao 2012). In the following, let $m\in\{+,-\}$ denote the valence of the message, i.e. if it is NWOM (-) or PWOM (+). In the style of Delre et al. (2007a/b) and van Eck et al. (2011), the credibility C_{it}^m of a message can be expressed as a linear combination of ISI_{it}^m and NSI_{it}^m perceived by network participant i:

$$C_{it}^m = \beta_i \cdot NSI_{it}^m + \left(1-\beta_i\right)\cdot ISI_{it}^m, \qquad \beta_i \in [0,1] \tag{3}$$

The individual parameters β_i depend on the general parameter β of the analysed market and vary around it. Like in the LTM, if the credibility of a message exceeds the individual threshold Φ_i^m of a person, then the person believes in this message. But usually, it may happen that a person receives the PWOM as well as the NWOM message whose credibilities both exceed his personal thresholds. In this case, he has to decide which message he wants to believe. Due to the negativity bias, NWOM messages are twice as strong as PWOM messages (Amini et al. 2011; Goldenberg et al. 2007; Sweeney et al. 2005). That means that in general $\Phi_i^+ \approx 2\cdot\Phi_i^-$ so that it is much easier to believe NWOM messages than to believe PWOM messages. Thus, it is not feasible to just compare the credibility of NWOM and PWOM messages or the differences between the credibilities and the according thresholds. Instead, the level to which each message's credibility exceeds its threshold must be used:

$$c_{it}^+ = \begin{cases} 1 & \text{if } \; C_{it}^+ \geq \Phi_i^+ \wedge (C_{it}^- - \Phi_i^-)/(1-\Phi_i^-) < (C_{it}^+ - \Phi_i^+)/(1-\Phi_i^+) \\ 0 & \text{else} \end{cases} \tag{4}$$

$$c_{it}^- = \begin{cases} 1 & \text{if } \; C_{it}^- \geq \Phi_i^- \wedge (C_{it}^- - \Phi_i^-)/(1-\Phi_i^-) > (C_{it}^+ - \Phi_i^+)/(1-\Phi_i^+) \\ 0 & \text{else} \end{cases} \tag{5}$$

The binary variables c_{it}^m indicate if network participant i believes NWOM ($c_{it}^-=1 \wedge c_{it}^+=0$) or PWOM ($c_{it}^-=0 \wedge c_{it}^+=1$) at time t. They can only be 1 if they exceed the according threshold Φ_i^m but not simultaneously at the same time. With the help of these variables, we can then calculate the spread of a message in the network:

$$S_t^m = \frac{1}{|V|} \cdot \sum_{i \in V} c_{it}^m \tag{6}$$

Normative Social Influence (NSI)

The normative social influence NSI_{it}^m depends on the network participant i's peer-group. The more neighbours of i forward the message m to him, the more he is driven to adopt this message and to believe it (Lascu et al. 1995). Because i's relationships to his neighbours j have different intensenesses b_{ij}, his neighbours are not equally important to him. The more intense a relationship between i and a neighbour j is, the more i is forced to believe j (De Bruyn and Lilien 2008; Ryu and Han 2009). Therefore, we consider the intenseness of relationships to those neighbours who forwarded a message for calculating NSI_{it}^m. For this, let $r_{ijt}^m \in \{0,1\}$ indicate if i has received message m from j in time step t and $r_{it}^m \in \{0,1\}$ indicate if i has received message m until time step t. Then, P_{it}^m denotes the share of peers that have forwarded message m to i weighted by the intenseness of their relationship b_{ij} perceived by i:

$$P_{it}^m = \frac{\sum_{j,(i,j)\in E} b_{ij} \cdot \sum_{\tau=1}^{t} r_{ij\tau}^m}{\sum_{j,(i,j)\in E} b_{ij}}, \qquad r_{ijt}^m \in \{0,1\},\ \ t \in [1,T] \tag{7}$$

Usually, already a small share of peers is sufficient to evoke a certain pressure but if a certain threshold is reached the perceived pressure increases only slightly. Therefore, we use the logistic function LF with a maximum value 1, δ being the steepness and ω the sigmoid's midpoint as a promoter for NSI_{it}^m that is only perceived by i if he has received the message until time step t:

$$NSI_{it}^m = r_{it}^m \cdot LF(P_{it}^m) \qquad \text{with } LF(x) = \frac{1}{1+e^{-\delta\cdot(x-\omega)}} \tag{8}$$

Informational Social Influence (ISI)

According to Allsop et al. (2007) and Sweeney et al. (2010), a message consists of at least two dimensions: A rational and an emotional dimension. The rational dimension concerns the argument quality (AQ) of a message that represents the degree to which a message is convincing because of its objective content (Cheung and Thadani 2012; Cheung et al. 2008). The higher AQ of a message is, the more credible it appears to the recipient (Cheung et al. 2009). The emotional dimension concerns the expressiveness (EX) of a message. The more (un-)satisfied a customer is, the more (negative) positive and therefore emotional will her message be (Buttle 1998). Recipients of a message will value EX and AQ in accordance to their expertise (Fan and Miao 2012; Sohn 2014; Park and Kim 2008) and opinion (East et al. 2008; Qiu et al. 2012) as well as to the sender's prestige (Cannarella and Piccioni 2008), expertise (Fan and Miao 2012; Cheung and Thadani 2012; Willemsen 2013), and the intenseness of the relationship with the sender (Davis and Khazanchi 2008; Akyüz 2013; Wang et al. 2012). Depending on the aforementioned characteristics, people value EX and AQ of a message differently, but a high AQ can to a certain degree counterbalance a low EX and vice versa (Galtung and Ruge 1965) The different valuation of EX and AQ shall be expressed by weighting factor $\gamma_i \in [0,1]$. Then, ISI_i^m can be calculated as a linear combination of the expressiveness $EX^m \in [0,1]$ and the argument quality $AQ^m \in [0,1]$ of message m if i has received the message before:

$$ISI_{it}^m = r_{it}^m \cdot \left(\gamma_i \cdot AQ^m + \left(1-\gamma_i\right) \cdot EX^m\right), \qquad AQ^m, EX^m, \gamma_i \in [0,1] \tag{9}$$

Forwarding Intention (FI) and Forwarding Probability (FP)

Once a network participant has received a message, he judges its credibility and decides whether to believe the message or not. If he values the content of the message and/or if he thinks that his neighbours will value it, he will decide to share the message with others (Sohn 2014). That means the more credible the message is (Sohn 2014) and the more the network participant i is tied to his peer j (Cheung and Lee 2012; Davis and Khazanchi 2008), the more he intends to forward the message. But credibility and intenseness are not two completely separate factors that both must be fulfilled independently of each other to form the forwarding intention. Instead, both factors are intertwined. On the one side, one factor is the prerequisite of the other. The more intense a relationship between two people is, the more likely a message will be forwarded (De Bruyn and Lilien 2008). But this only holds if the credibility of the message is high enough (Pescher et al. 2013) because people communicate to shape their reputation in their peer group (Lampel and Bhalla 2007). And if the credibility is low, forwarding such a message threatens the sender's reputation (Pescher et al. 2013). On the other side, intenseness and credibility can act additively. If the credibility is high, it is very likely that a message is forwarded irrespective of the relation between people. The intenseness of the relation will then increase the likelihood of forwarding. The same holds if the intenseness is high. Then, people will forward a message no matter of its credibility. The credibility will just drive the network participant more likely to forward the message. In other words, to make a network participant i forward a message to j, there needs to be at least a minimum of credibility of the message and a certain intenseness between i and j. But otherwise, the more intense the relationship between i and j is, the higher the forwarding intention of i will be irrespective of the message's credibility and vice versa. Therefore, we do not use a simple linear combination of credibility and intenseness but a combination of mutual dependency and enhancement:

$$FI_{jit}^{m} = \eta \cdot b_{ij} \cdot C_{it}^{m} + (1-\eta) \cdot \left(b_{ij} + C_{it}^{m} - b_{ij} \cdot C_{it}^{m}\right), \qquad \eta \in [0,1] \tag{10}$$

A prerequisite for forwarding a message is that the sender thinks the message will be new to the recipient (Falkinger 2007). The older a message is, the more unlikely it is that the recipient does not know about it. Hence, we can conclude that the older a message is, the more unlikely it is that a message is forwarded to others. Such an aging is assumed to reduce the topicality of a message exponentially (Nugrohu et al. 2015). But even if the message is completely new, the network participant will only forward the message if he is not convinced of the contrary. That means only if he believes the message or is unconvinced, he will decide whether to forward this message to his neighbours. Let T^{m} be the time step when message m was initially launched, and $T_{1/2}^{m}$ be the half-life of the message. Then, the forwarding probability FP_{jit}^{m} that indicates the likelihood that i forwards message m after time step t to j is calculated as follows:

$$FP_{jit}^{+} = \left(\left(1-c_{it}^{-}\right) \cdot c_{it}^{+} + \left(1-c_{it}^{+}\right)\left(1-c_{it}^{-}\right)\right) \cdot FI_{jit}^{+} \cdot e^{-\frac{\ln(2)}{T_{1/2}^{+}}\left(t-T^{+}\right)} \tag{11}$$

$$FP_{jit}^{-} = \left(\left(1-c_{it}^{+}\right) \cdot c_{it}^{-} + \left(1-c_{it}^{+}\right)\left(1-c_{it}^{-}\right)\right) \cdot FI_{jit}^{-} \cdot e^{-\frac{\ln(2)}{T_{1/2}^{-}}\left(t-T^{-}\right)} \tag{12}$$

Forwarding Decision

Finally, network participant i will forward message m to his peer j in time step t+1 with probability FP_{jit}^{m}. Communication serves people to shape their reputation in their network (Lampel and Bhalla 2007). If network participant i forwards message m to his peer j twice, he risks that his reputation decreases. Therefore, i will forward m only if he had not forwarded m in one of the time steps before. A message m is only forwarded in time step t+1 if i has received the message in time step t. That means if he received NWOM but not PWOM his decision is only on the NWOM message and vice versa. The initial seeds of the NWOM as well of the PWOM message cannot be influenced. In sum, the binary variables that indicate the forwarding of a message from i to j in time step t+1 (r_{jit+1}^{m}) and the reception by j until time step t+1 (r_{jt+1}^{m}) are calculated as follows:

$$r_{jit+1}^{m} = \begin{cases} 1 & FP_{jit}^{m} \geq \tilde{u}_{jit}^{m} \ \wedge \ \sum_{\tau=1}^{t} r_{ji\tau}^{m} = 0 \ \wedge \ \sum_{i,(i,j)\in E} r_{ijt}^{m} \geq 1 \\ 0 & \text{else} \end{cases}, \quad \tilde{u}_{jit}^{m} \text{ is a uniformly distributed random variable} \tag{13}$$

$$r_{jt+1}^{m} = \begin{cases} 1 & \sum_{i,(i,j)\in E} \sum_{\tau=1}^{t} r_{ji\tau}^{m} \geq 1 \\ 0 & \text{else} \end{cases} \tag{14}$$

Numerical Analysis

We analysed our competitive diffusion model in a simulation study. According to Granovetter (1973), social networks can be characterised by two components: strong connected local sub-networks where the network participants resemble each other and so-called bridges or short-cuts that connect the sub-networks with each other so that a fast flow of information is possible. So-called small world networks developed by Watts and Strogatz (1998) also possess these characteristics so that they are well suitable to study the diffusion of information instead of using big real-world networks (Onnela et al. 2007). Therefore, we study our diffusion model with the help of small world networks with 1000 vertices and a lattice parameter of six. Then, the average path length (APL) of the small world network is approximately six and therefore resembles the APL of real networks (Dodds et al. 2003; Milgram 1967). The rewiring probability is set to 10% in order to create networks with realistic behaviour and dynamics.

Each experiment consisted of 500 networks that were randomly generated. The simulation was stopped when no more messages were forwarded. The parameters that we used during the experiments are as follows: The expected values (μ) and standard deviations (σ) of the individual credibility thresholds are $\mu(\Phi_i^-)=0.25$, $\mu(\Phi_i^+)=0.5$, $\sigma(\Phi_i^-)=0.0625$, $\sigma(\Phi_i^+)=0.125$ and of the weighting factor between AQ and EX $\mu(\gamma_i)=0.5$, $\sigma(\gamma_i)=0.125$. The intenseness is exponentially distributed with expected value $\mu(b_{ij})=0.2$. For the steepness of the logistic function to calculate NSI we used $\delta=20$ and for the sigmoid's midpoint $\omega=0.25$. The weighting between intenseness and credibility in FI is $\eta=0.5$.

Non-Competitive Setting: Influence of Half-life, Market, and Informational Value

To analyse the influence of the market parameter β and the half-life $T_{1/2}^m$ on the message spread, we use an NWOM message with the highest possible informational value $EX^- = AQ^- = 1$ in the first step. In general, the results remain the same if we observe the spread of a PWOM message. As we can see in Figure 1a), if there is no aging, the message spread S_T^- of such a strong NWOM message is nearly 100% in all markets. If $T_{1/2}^- = 1$, the most progressive aging, that means the message loses 50% of its topicality in one time step, S_T^- is between 1% and 3% approximately. Between these extreme aging factors, the NWOM spread is significantly higher in individualistic markets ($\beta \to 0$) than in collectivistic markets ($\beta \to 1$) with a maximum difference of 90.52%-points at $T_{1/2}^- = 14$. The reason is that in individualistic markets the content of a message (i.e. ISI consisting of EX and AQ) is higher valued than the opinion of peers (i.e. NSI). Because of this, the credibility of the message is perceived as high from the beginning on which in turn causes the message to be forwarded more often and results in a wider spread of the message throughout the network. In collectivistic markets, it is much more difficult for messages to spread because there people are more oriented to the behaviour of others than to the message's content. Therefore, the credibility of the message is very low at first although $EX^- = AQ^- = 1$ as in the beginning nearly no peer has sent the message. Not before a certain number of peers have forwarded the message, the credibility increases. When there was no aging set, the NWOM message indeed took significantly longer in the most collectivistic market to reach its final spread than in the most individualistic market (β=0, T=18.65 vs. β=1, T=35.91).

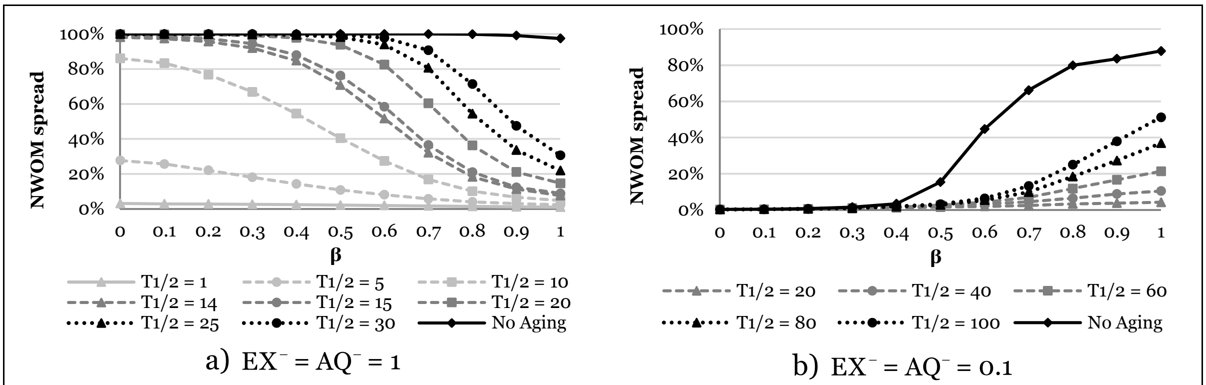

Figure 1. Variation of market parameter for different values of half-life

We performed the same experiments as above for a much weaker message with $EX^- = AQ^- = 0.1$. As we can see in Figure 1b), in individualistic markets with $\beta < 0.4$ such a message can hardly spread. Only in collectivistic markets with $\beta \geq 0.4$, the weak message can survive. If the message lasts long enough, it can reach a significant level of network penetration. But note that the half-lives are increased in comparison to the first experiments depicted in Figure 1a). In the following, we will therefore concentrate on two markets: an individualistic market with β=0.1 and a collectivistic market with β=0.4. If not mentioned otherwise, the half-life of a message is set to $T^m_{1/2} = 10$. That means that messages lose 50% of their topicality after 10 time steps. Choosing these values, the small world networks that we use here mimic the dynamics of much larger networks since it is highly unlikely that even a strong NWOM message can reach a spread close to 100% in big OSN such as Facebook or Twitter.

Now let us have a look at the expressiveness and argument quality of a message. Since empirical results are missing how people weight these factors, the individual weighting parameter γ_i is generated from a truncated normal distribution with an expected value of 0.5. Hence, EX^m and AQ^m are on average perceived as equally strong. Because of this, any combination of EX^m and AQ^m is interchangeable. More precisely, the results of experiments with $AQ^m = x$ and $EX^m = y$ will in general equal the results of $AQ^m = y$ and $EX^m = x$. Therefore, we always assign the same values to EX^m and AQ^m in the following and call the level of EX^m and AQ^m the informational value of a message.

In Figure 2, EX^- and AQ^- are varied in steps of 0.1. For values of EX^- and AQ^- below 0.4, the NWOM spreads of the collectivistic and the individualistic market are quite similar. With regard to expected value and standard deviation, the greatest similarity occurs for $EX^- = AQ^- = 0.3$. With stronger NWOM messages, the difference between the markets increases. In order to examine the similarities and differences between both markets in terms of collective behaviour and spread dynamics, we analyse three cases in more detail: a weak ($EX^- = AQ^- = 0.3$), a medium ($EX^- = AQ^- = 0.6$), and a strong ($EX^- = AQ^- = 1.0$) NWOM message.

	β=0.1		β=0.4	
EX⁻ and AQ⁻	Expected Value	Standard Deviation	Expected Value	Standard Deviation
0.0	0.15%	0.08%	0.57%	0.35%
0.1	0.30%	0.17%	0.86%	0.48%
0.2	0.93%	0.51%	1.52%	0.82%
0.3	**2.80%**	**1.59%**	**2.51%**	**1.32%**
0.4	6.29%	3.54%	4.60%	2.58%
0.5	10.78%	6.00%	8.01%	4.36%
0.6	19.20%	9.32%	12.92%	6.60%
0.7	**33.41%**	**12.64%**	**20.17%**	**8.83%**
0.8	52.01%	14.15%	29.16%	11.43%
0.9	68.16%	13.62%	41.05%	13.78%
1.0	**82.62%**	**10.95%**	**54.75%**	**14.67%**

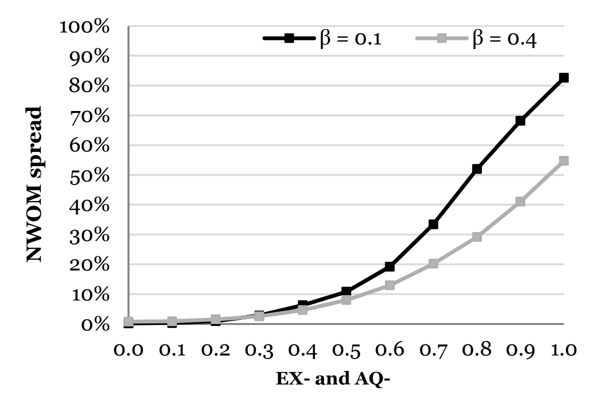

Figure 2. NWOM spread for different values of EX^- and AQ^-

Competitive Setting: Influence of Reaction Time and Informational Value

In the competitive case, a PWOM message is launched as a countermeasure to restrict the NWOM spread. Three parameters of the PWOM message can be influenced: The informational value, i.e. EX^+ and AQ^+, the delay between the first occurrence of the NWOM message T^- and the launch time T^+ of the PWOM message, i.e. the reaction time $T^R = T^- - T^+$, and the number of seeds who initially inject the network with the PWOM message. In the first step, we have a look at the influence of reaction time and informational value on the efficiency of the PWOM message, measured by the final NWOM spread S^-_T. For this, we vary the reaction time $T^R \in \{0,1,2,4,8,16,32\}$ and the informational value of the PWOM message by steps of 0.1. The results are depicted in Figure 3.

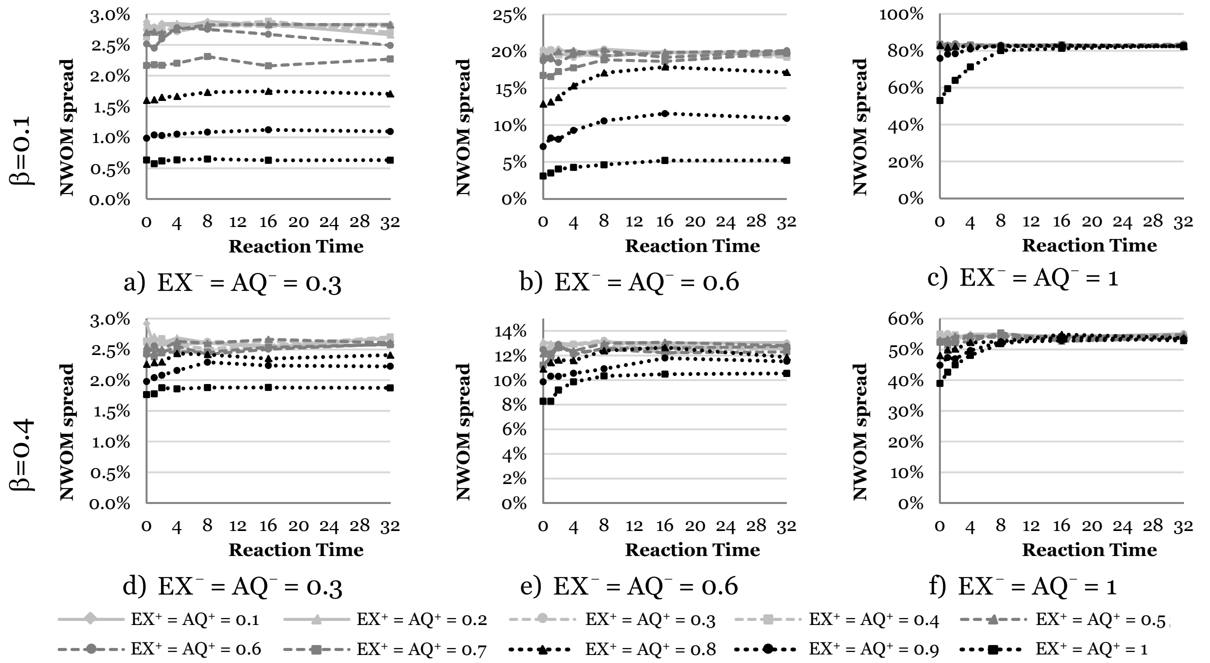

Figure 3. NWOM spread for different reaction times and one PWOM seed

If the NWOM message is weak as in case a) and d), the reaction time is not important no matter if the market is individualistic or collectivistic. Even with reaction time T^R =32, the NWOM spread is almost the same as with T^R =0. In contrast, the informational value (i.e. EX^+ and AQ^+) of the PWOM message plays a much more important role. PWOM can only restrict NWOM if the informational value of the PWOM message exceeds a certain threshold. For instance, in the individualistic case a) EX^+ and AQ^+ need to be greater than 0.6 and therefore more than twice as strong as the NWOM message in order to reduce the negative spread significantly. The stronger the NWOM message is, the higher the threshold is.

If the NWOM message is stronger, the reaction time plays a more critical role. As we can see, if the response is delayed, the efficiency of the PWOM message declines. This holds until T^R exceeds a certain threshold. After that point in time, no more efficiency losses can be observed. The stronger the PWOM answer is, the smaller are the efficiency losses caused by longer reaction times. However, even the strongest PWOM message can lose all of its reduction effects if the reaction time is too long in case that the NWOM message is at its highest. But a faster response can hardly outweigh the gains of a better informational value. If the informational value of the PWOM message is increased, it restricts the NWOM spread better than a weaker message that was released earlier.

These observations hold for the individualistic as well as for the collectivistic market. The main difference is that in collectivistic markets the NWOM spread is lower and the restricting PWOM effects are weaker in absolute and relative terms. For example, PWOM messages equally strong as the NWOM message reduce the NWOM spread in collectivistic markets less than in individualistic markets. Therefore, in general, it is more difficult to restrict NWOM in collectivistic than in individualistic markets.

Competitive Setting: Influence of Number of Seeds

Now, the last parameter that can be influenced, the number of seeds, is varied. As we could see in the previous section, the PWOM messages usually should be of higher informational value than the NWOM messages to fight against. Therefore, we restrict our analyses to PWOM messages with $EX^+ \geq 0.6$ and $AQ^+ \geq 0.6$ except for the case of a weak NWOM message. In this case (Figure 4a and 4d) we can see that increasing the number of seeds does not help if the PWOM message is too weak even if the NWOM message was also that weak. The same holds for a medium or strong NWOM message that is fought with a weak PWOM message (not depicted). Then, the PWOM message has barely any effect in both markets. If a medium NWOM message (Figure 5) is fought with an equally strong PWOM message, the effect is slightly different between the individualistic and the collectivistic market. In the former (Figure 5a), only a high number of seeds (8 or 16) can restrict the NWOM spread in the first four time steps. After that, using more seeds has nearly no effect. In the latter (Figure 5d), a slight effect remains for a high number of seeds even after time step 4. That means that increasing the number of seeds can reduce the NWOM spread only if the informational value of the PWOM message is not too weak.

All in all, a greater reaction time does not reduce the relative efficiency gains between different numbers of seeds significantly if the NWOM message is weak (Figure 4) or medium (Figure 5). In contrast, when the NWOM message is strong (Figure 6), the gains of activating more seeds decline much more with increasing reaction time. In general, this holds for both markets. But increasing the number of seeds seems to have a greater impact in individualistic markets if the NWOM message is weak or medium. In these cases, the NWOM spread is reduced relatively more in the individualistic market when using more seeds in comparison to using just one seed. Usually, one would expect that in collectivistic markets the more seeds are used, the more the opinions can be changed because of the greater influence of NSI. Hence, this result is somewhat surprising. The reason that this effect could not be observed is that in our experiments the seeds are selected randomly. Because of this, the seeds are usually not in the neighbourhood so that the effect of using more seeds diminishes. The messages spread due to their (weak or medium) informational value which has a higher effect in the individualistic market. There, more seeds make the PWOM reach more people until the NWOM message is not too strong. Only if the NWOM message is strong (Figure 6), the picture inverts. While the efficiency gains between different numbers of seeds in the individualistic market nearly vanish completely with increasing reaction time, there is still a slight reduction in the collectivistic market. The reason is that due to its high informational value, the PWOM message spreads from the beginning also in the collectivistic market and therefore creates convinced groups in the network. Then, when the NWOM message reaches the network participants of these groups, the peer pressure saves them from believing the NWOM message while in the individualistic market ISI is of greater importance so that the high informational value of the NOWM message makes the network participants more likely to switch their opinion.

If we compare the final NWOM spreads countered by one good PWOM message but launched with delay and those countered earlier or rather immediately by a message with less informational value but more seeds, the stronger PWOM message mostly outperforms the weaker message. Concerning the weak NWOM message, in the individualistic market, the best PWOM message (Figure 4c) launched by one seed with a response time of $T^R=32$ restricts the NWOM spread more than the second best message (4b) launched immediately by 16 seeds ($S_T^-=0.61\%$ versus $S_T^-=0.63\%$). In the collectivistic market, the strong PWOM message launched by one seed in $T^R=32$ (4f) still outperforms the medium message launched immediately by four seeds (4e) ($S_T^-=1.87\%$ versus $S_T^-=1.89\%$) or in $T^R=4$ by eight seeds ($S_T^-=1.93\%$).

Concerning the medium NWOM message, the best PWOM message with $T^R=32$ and one seed (5c and 5f) outperforms the second best message launched immediately by four seeds ($S_T^-=4.84\%$ versus $S_T^-=6.01\%$), after two time steps by eight seeds ($S_T^-=5.30\%$), and after four time steps by 16 seeds ($S_T^-=4.91\%$) in the individualistic market (5b). In the collectivistic market, this message (5f) outperforms the second best message (5e) launched immediately by one seed ($S_T^-=10.21\%$ versus $S_T^-=11.30\%$), after four time steps by two seeds ($S_T^-=10.84\%$), and after eight time steps by four seeds ($S_T^-=10.93\%$). If we double the number of seeds for the best message, it is better than the second best message launched after one time steps by two seeds ($S_T^-=9.43\%$ versus $S_T^-=9.73\%$), and after four time steps by four seeds ($S_T^-=9.53\%$).

Even for the strongest NWOM message (Figure 6) we can observe a similar result. Please note that the second and third best PWOM messages are only slightly weaker than the best PWOM message. In the individualistic market, if the strongest PWOM message (6c) is launched with $T^R=32$, it outperforms the second best message (6b) launched by two seeds after eight time steps ($S_T^-=81.99\%$ versus $S_T^-=82.34\%$) and the third best message (6a) launched immediately by two seeds ($S_T^-=82.61\%$). If the best message is launched with $T^R=4$, it achieves better results than the second best message launched immediately by two seeds ($S_T^-=72.09\%$ versus $S_T^-=73.03\%$) and widely outperforms the third best message launched immediately by 16 seeds ($S_T^-=76.01\%$). In the collectivistic market, the best PWOM message (6f) launched with $T^R=32$ is better than the third best message (6d) launched by one seed after eight time steps ($S_T^-=52.83\%$ versus $S_T^-=53.63\%$) and has nearly the same result like the second best message (6e) launched after eight time steps (S_T^-=52.62%). If the best message is launched with T^R=2, it outperforms the second best message launched immediately by one seed (S_T^-=43.54% versus S_T^-=45.19%) and the third best message launched immediately by two seeds (S_T^-=44.26%).

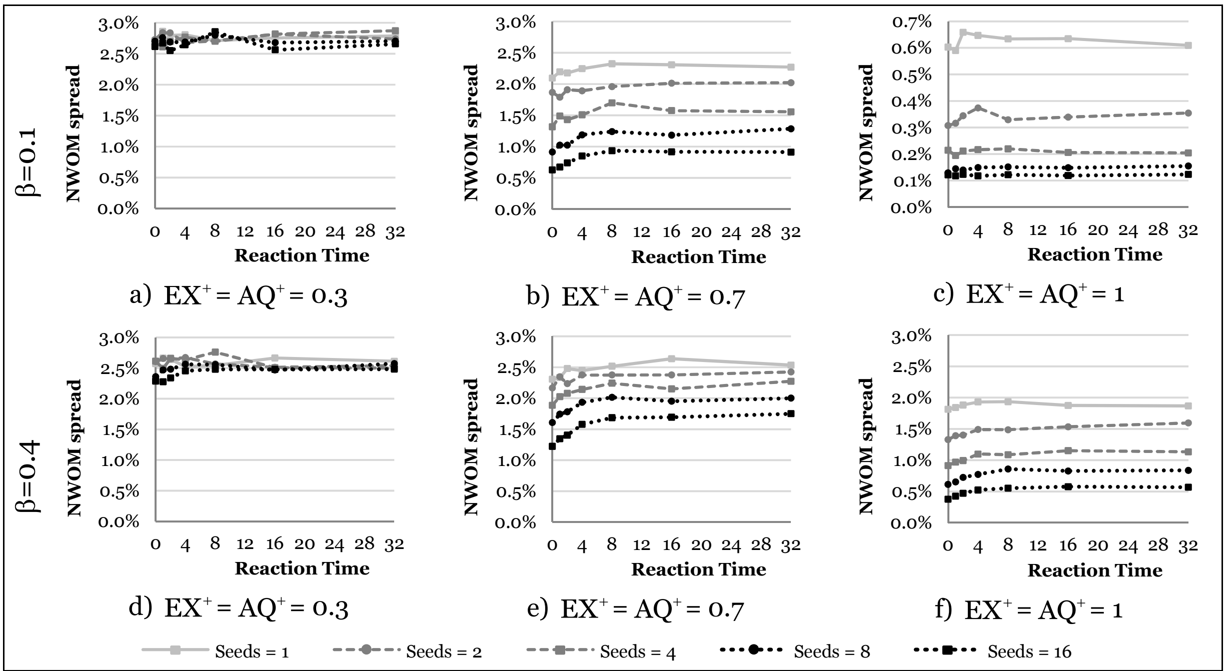

Figure 4. NWOM spread for EX^-=AQ^-=0.3 and different number of PWOM seeds

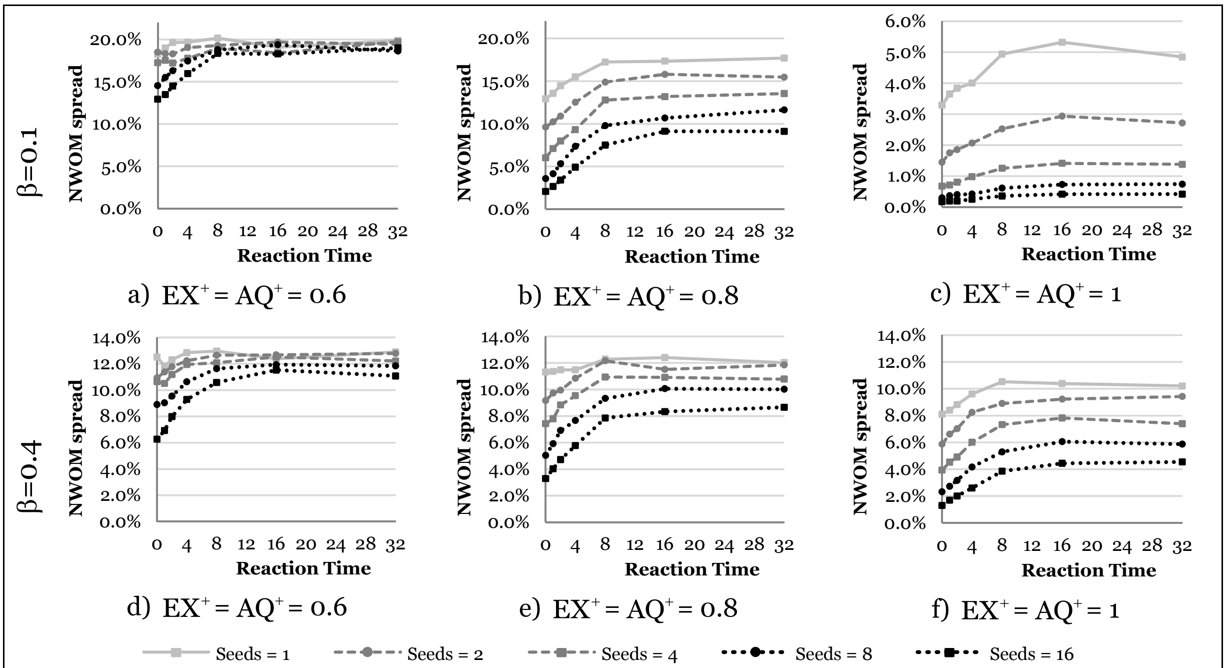

Figure 5. NWOM spread for EX^-=AQ^-=0.6 and different number of PWOM seeds

Interestingly, the efficiency gains of doubling the number of seeds are in the most cases, if any, only linear and do not always bring the same results. In the individualistic market for example, doubling the number of seeds from 8 to 16 brings only little gains in case of weak and medium NWOM messages that are countered with a strong PWOM message (Figure 4c and 5c). In particular when the NWOM message is strong, the gains of using more seeds mostly vanish with greater reaction time. That means that using more seeds can hardly compensate the informational value and only partly the reaction time. But a strong PWOM message can to a certain degree compensate reaction time and number of seeds.

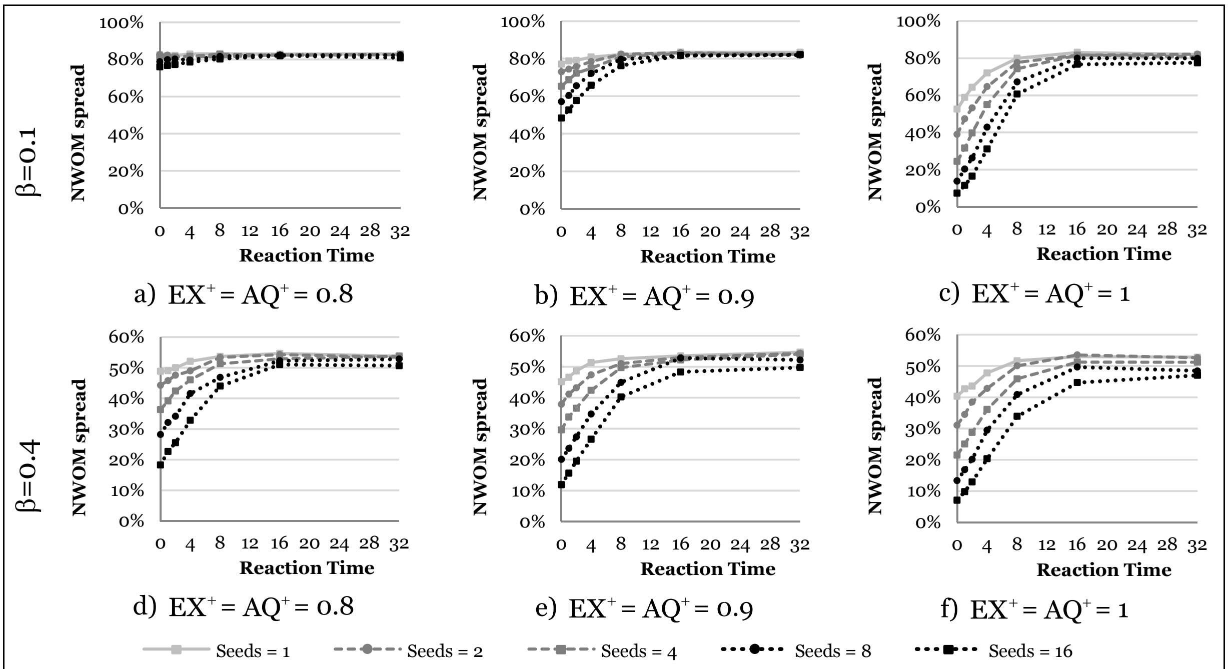

Figure 6. NWOM spread for $EX^{-}=AQ^{-}=1$ and different number of PWOM seeds

Discussion

Conclusion

In this paper, we have presented a novel diffusion model for the spread of information that tries to overcome some shortcomings of the popular diffusion models LTM and ICM. To the best of our knowledge, this model is the only one in this field that considers not only a delay between the NWOM and the PWOM message and a potential change in a network participant's opinion, but also aging of messages, different kinds of markets, and the content of the message. Our results show that these factors influence the spread of NWOM as well as PWOM significantly. In individualistic markets (e.g. food) where people are much more oriented to the quality of arguments than to the behaviour or opinion of their peers, a weak message with bad arguments can hardly spread even if there is no aging (the message keeps always up-to-date). In contrast, after a while such a weak message can spread widely in very collectivistic markets (e.g. fashion). That means that although a message is weak and may seem to be forgotten after a while, it may suddenly reoccur in collectivistic markets and reach a significant spread. Concerning strong messages of high informational value, these always find their audience except we are facing a very vibrant market with permanently updated news where the half-life of messages is very short. But even then, we can observe a certain spread.

Our analysis has shown that it is not always important to react quickly on NWOM messages as Mochalova and Nanopoulos (2014) have stated and what one would intuitively assume. This also holds for a greater number of seeds that are used to inject the network with the counteracting message. Instead, the informational value plays a much more important role. A well designed PWOM message has a much greater effect on the NWOM spread than a fast reaction or a counteraction with multiple seeds. To a certain degree, such a strong PWOM message can compensate a long reaction time and/or multiple seeds. If the counteracting PWOM message is badly designed, the restricting effects are marginal. This is in line with Trpevski et al. (2010) who found that for non-dominant message it is difficult to survive. Although we did not study dominance, the stronger message can be seen as the dominant and the weaker as the non-dominant message. However, in contrast to Trpevski et al. (2010), we found in additional experiments that the starting point of messages matters. If we used PWOM seeds in direct neighbourhood to the NWOM seeds, the PWOM message usually restricts the NWOM spread better than with a global injection. This finding is in line with Easley and Kleinberg (2010) who found that densely connected clusters can stop the information flow in networks. If the NWOM seed is quickly surrounded by PWOM believers, the NWOM message cannot spread to other parts of the network and infect them.

Managerial Implications

Several lessons can be learned from our study. First of all, reacting to NWOM with a badly designed PWOM message is not worth the money and should always be avoided. A weak PWOM message has barely an effect on the NWOM spread. On the contrary, such a weak message may provoke adverse effects. It is conceivable that a badly designed message evokes a second and even stronger wave of NWOM with greater EX and AQ (Lee and Song 2010; Mochalova and Nanopoulos 2014). This new NWOM wave would then completely destroy any effect of the PWOM reaction and worsen the whole situation. However, this more game theoretical approach was not considered within this paper. Therefore, firms should always try to answer with a message as good as possible. The informational value of a PWOM message outperforms any other effects. It is always better to react with a substantially good message than with a weaker one but launched earlier or with more seeds. The effect of a good message is much greater than a fast response. Therefore, firms should take their time to design a good message and risk a further spread of the NWOM message because a later but good PWOM message can fight the NWOM message much more efficiently than a badly designed message can do. In particular, when the NWOM message is weak, the reaction time is of no importance but the informational value still is. With increasing informational value of the NWOM message, firms have to react more quickly. If it is not possible to react immediately, the later message can be supported by multiple seeds. But the use of multiple seeds is expensive. For any time step that the message is launched later, the number of seeds must be increased disproportionally. In addition, if the NWOM message is very strong, after a while it is not possible to balance the time loss with more seeds. Therefore, if a firm faces justified complaints that are presented well with high quality, it is crucial to react quickly and well. Then, the best way seems to be an apology (EX) and an adequate compensation (AQ).

The NWOM spread in individualistic markets is greater than in collectivistic markets. Therefore, firms of these markets should regularly monitor their market so that they can react on upcoming NWOM in time. But in return, NWOM can also be fought more easily be it with a better designed message or more seeds. As a consequence, individualistic markets are also more prone to viral marketing. In contrast, the sometimes slow spread of NWOM in collectivistic markets can be a challenge. Already forgotten messages can suddenly reoccur. Then, it is quite difficult to fight against it. Therefore, while in individualistic markets weak messages hardly reach a significant spread, in collectivistic markets even weak messages should be countered, in particular when aging is low. But the advantage is that the firm can take much time to design a good PWOM message.

Irrespective of the time delay, the main question for firms is how to create a good message concerning AQ and EX. In fact, the operationalisation is not trivial. AQ is affected by the number and quality of arguments used in a message. Two different messages with the same number of arguments are usually not perceived as being equal. Instead, the perceived quality of the message depends on how the arguments are perceived as suitable, valuable, and truthful by the receiver and this in turn depends on the strength of the argument itself and on the value system of the reader (Staab 1990). For a better understanding, let us have a look at the example of user generated hotel ratings and two different arguments one saying that the rooms are not clean, the other that the breakfast is poor. Depending on the value system of the reader, either the cleanliness or the breakfast problem is given more importance in general. Concerning the strength of the arguments, both arguments can be a written statement or can be underlined by a photograph taken during a stay in the hotel. A photograph showing the dirt in the rooms or the unappetising breakfast can be seen as a proof of facts and therefore makes the argument very strong. A written statement on the contrary is not easily verifiable for the reader. There, the strength of the argument depends on how the statement is written, i.e. words used, length, presentation, mistakes etc.

While the individual value system of readers and their perception of an argument's strength cannot be assessed directly, a firm can judge both factors indirectly. If different social media managers rate the strength and importance of an argument on a Likert scale, one can assume that the average estimation is near to the readers value system and perception. Concerning EX, the situation is more complicated. The expressiveness of an NWOM message can be measured by the number of negative words in relation to the message length. The more negative words are used, the more the message expresses the negative attitude of its author. But measuring EX of a PWOM message is much more difficult because EX is a construct consisting of many different dimensions. A message can be rational or emotional (Ravichandran et al. 2015), narrative or analytical (Van Laer and De Ruyter 2010), empathic or sober etc. In addition, depending on the intention of the PWOM message, different dimensions should be addressed (Van Laer and De Ruyter 2010). Many authors have already examined what kind of messages or videos concerning the expressiveness go viral and which are forwarded more likely (e.g. Botha and Reynecke 2013; Chiu et al. 2014; Eckler and Bolls 2011; Radighieri and Mulder 2012; Van Laer and De Ruyter 2010), but they did not give advice how to measure the different message characteristics they investigated. As a result, firms can therefore either assess each dimension separately or the expressiveness of a message as a whole letting social media managers judge EX or its dimensions on a Likert scale and then use the average value. The importance of each dimension can be assessed in the same way.

Limitations and Future Research Directions

As always, there are also some limitations. First of all, we presented a simulation study with pure numerical data. To validate the proposed model, future research should focus on confirming our findings empirically. For this, real world cases should be observed and analysed if the model can reproduce the developments of the real world scenarios. However, before doing this, realistic values for several parameters used in the model have to be found. For example, we used several weighting factors (e.g. γ_i for weighting EX and AQ) but until now there is no empirical evidence for their values. We therefore treated these factors equally so that the values of EX and AQ are exchangeable in the current state. But it would be interesting to analyse if messages of different EX and AQ must be fought differently. It is conceivable, that an NWOM message with great EX and low AQ can be fought by PWOM messages with high AQ and low EX. In addition, the weighting between EX and AQ may also depend on the market. These factors can be analysed using laboratory experiments that distinguish between different levels of AQ and EX, use scenarios in different markets like for smartphones, books, food, or fashion and observe to whom network participants forward different messages and why. Secondly, we used small world networks instead of real networks. For this, the number of seeds can only be seen in relation to other experiments. Conclusions on the number of seeds needed for real networks cannot be drawn. Thirdly, the forwarding mechanism is simplified due to practical considerations. We did not consider that messages can be changed when forwarded so that AQ and EX change in time. This would pose the question how to handle the different messages at each network participant. Moreover, the forwarding process is only triggered by messages of the same valence. That means that a network participant decides only on that message to forward that he received in the current time step. For example, if he receives PWOM he decides to forward PWOM no matter if he received the NWOM message in former time steps. But it is conceivable that when he receives PWOM and has also received NWOM before that he decides to forward the NWOM instead of the PWOM message. This would draw a much more realistic picture and also consider backlashes to PWOM campaigns. Fourthly, we did not take into account that after a while people are more convinced than in the beginning. This would make it much more difficult to convince a person of the contrary. However, to a certain degree, aging can depict this phenomenon. Fifthly, we did not include individual characteristics (expertise, opinion, or credibility) of the network participants into the model directly. The reason is that including individual characteristics would have made the model even more complex but would not have added more value and explanatory power to the analysis because to a certain degree, these characteristics are depicted by the individual weighting factor γ_i . In addition, firms usually also do not know exactly about the characteristics of the network participants. Finally, we did not compare our proposed model to the existing models. There may be differences in the message spread in the competitive as well as in the non-competitive case. In particular, it will be interesting to observe if our proposed model really draws a more realistic picture with regard to real life scenarios.

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