SILENCE IS GOLDEN – WHEN FIRMS SHOULD REACT TO NEGATIVE WORD OF MOUTH

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Research paper

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Abstract

With the advent of online social networks such as Facebook or Twitter, negative messages about a product or an enterprise can spread faster, reach a greater degree of dissemination, and will be able to influence the attitude and behaviour of customers. Quickly, a serious amount of economic damage can arise caused by such negative word of mouth. This paper examines various strategies on how firms can adequately cope with and react to negative word of mouth in online environments. For this, a diffusion model is presented that incorporates not only the content of a message and aging but also the phenomenon of triggering older messages. To evaluate the activities and reactions both technical and economic indicators are used. The results show that it is advantageous for firms to invest more time in designing a good counter message than to react as quickly as possible or to use more seeds. In addition, reacting with a big number of seeds can even cause more damage than just doing nothing. In some situations, it is therefore beneficial for firms not to take any measure.

Keywords: Information Diffusion, Online Firestorms, Social Networks, Word of Mouth.

1 Introduction

Traditionally, consumers favour using word of mouth for gathering information about products over other media and advertisement channels, since it is perceived as more reliable and trustworthy (Cheung and Thadani, 2012; Hennig-Thurau et al., 2004; Katz and Lazarsfeld, 1955). Electronic word of mouth (EWOM) empowered by online social networks (OSN) has considerably simplified the process of exchanging customer experiences (Yoo et al., 2015; Willemsen, 2013). It helps consumers in making better purchase decisions by reducing perceived purchase risks (Willemsen, 2013; Bambauer-Sachse and Mangold, 2013; Jung and Kim, 2012). In this regard, negative electronic word of mouth (NWOM) is found to significantly reduce the purchase intention of consumers, while positive electronic word of mouth (PWOM) increases it (Van Noort and Willemsen, 2012; Cheung and Thadani, 2012; Fan and Miao, 2012; East et al., 2008). Due to the so-called negativity bias, NWOM is perceived as being more credible than PWOM (Rozin and Royzman, 2001). Thus, the overall impact of NWOM on the purchase intention of consumers is greater in comparison to PWOM (Lee et al., 2008). Research has also shown that negative messages can propagate faster and reach a higher spread in OSN which can result in an online firestorm tremendously harming a firm’s reputation (Mochalova and Nanopoulos, 2014; Pfeffer et al., 2014; Cannarella and Piccioni, 2008). Firms have therefore recognised the increased relevance of EWOM and the necessity of both monitoring and generating it on OSN (You et al., 2015; Van Noort and Willemsen, 2012). Inducing PWOM enables firms to improve their reputation and increase the awareness level for their brands (Pfeffer et al., 2014). However, nega-
tive messages disseminated by dissatisfied customers can lead to significant financial losses and therefore represent a great threat to a firm’s success (Van Noort and Willemsen, 2012). It is not obvious in which way a firm should react to NWOM (Pfeffer et al., 2014). A firm needs to trade off the costs for satisfying a dissatisfied customer against the damage an NWOM message of this customer might cause. A quick reaction might help in resolving the issue and prevent further damage (Van Noort and Willemsen, 2012). But if a publicly issued statement is not well received by OSN members, it can easily backfire by entailing a second wave of negative messages that might increase the initial damage (Mochalova and Nanopoulos, 2014; Pfeffer et al., 2014). While Beşer et al. (2016) have shown that it is better to react later with a well-designed message instead of reacting quickly and neglecting the message’s quality, it is still in question if a reaction is always appropriate and recommendable. Therefore, this paper aims at answering the following research question:

RQ: In which situations is it mandatory to react to NWOM and under which circumstances is it better to resign from taking any measures?

Thereby, this paper contributes to the literature of competitive word of mouth in the following ways. First of all, we introduce a so-called range of indifference between the NWOM and the PWOM message. That means that if both messages are credible, the recipient is not forced to believe one of the messages but can stay indifferent until he is convinced by his peers. Secondly, a message cannot only trigger messages of the same valence but also of the opposite. This depicts the situation when firms react to NWOM with a badly designed PWOM message so that recipients are upset and spread the NWOM message instead of the PWOM message. And thirdly, this paper is, to the best of our knowledge, the first paper that analyses the economic consequences of two competing messages. For this, we assume that people have a certain purchase intention and analyse how NWOM and PWOM messages affect the resulting purchase decision.

The remainder of this paper is structured as follows: the next section gives a comprehensive overview of the related literature in the research field of information diffusion in OSN. In section 3 we introduce our model that extends the existing diffusion models. Due to its complexity a numerical analysis is carried out in section 4 to examine consumer behaviour in various scenarios. Section 5 summarises the main findings, deduces managerial implications, discusses limitations, and points out future research directions.

2 Literature Review

This paper mainly contributes to the literature of competitive word of mouth in OSN. The general setting is that at least two concurrent messages spread in a network each one aiming for the conviction of the network participants. Messages can also be seen as firms or products competing for the customers (=networks participants) of a market (=network). In this regard, Bharathi et al. (2007) have shown that first and second mover can both find an optimal set of seeds for influencing the network. However, Pathak et al. (2010) have shown that only a certain number of concurrent messages/products can survive in a given market. But despite of this, if firms compete, they will usually operate in the same markets because this will maximise the total spread (Goyal and Kearns, 2012). Interestingly, being the first in the market is not always better. Even with a limited budget, the second mover can outperform the first mover under certain circumstances (Kostka et al., 2008; Carnes et al., 2007). While the non-competitive problem of maximising the influence in a network can be solved in acceptable computational time (Kempe et al., 2005; Kempe et al., 2003), already small changes to the original influence maximisation problem hamper an approximation of the optimal solution (Chen et al., 2011; Borodin et al., 2010).

Except for Chen et al. (2011), the aforementioned papers all assume the different messages to be equal in their strength and credibility. In reality, this assumption does not hold. A lie for example is usually discovered when the truth is revealed (Nguyen et al., 2012) and negative messages are said to be twice
as strong as positive messages (Anderson, 1998; Heskett et al., 1997; Bone, 1995). Therefore, several papers aim for blocking the spread of an opposing negative message and saving as many people as possible from receiving this message instead of maximising the spread of the own positive message. In Budak et al. (2011) and Nguyen et al. (2012), the positive message is assumed to be stronger than the negative one. This indeed mostly holds for the truth versus lie situation, but usually the situation is less obvious. If for example rumours about a product’s quality spread like in Chen et al. (2011), people cannot judge with certainty which message is correct. Moreover, both parties may be correct to some extent so that it is hardly possible to judge. In this case, the negativity bias (Rozin and Royzman, 2001) takes effect making people more likely to believe and forward the negative message. In this case, the non-dominant message often hardly survives in the network (Trpevski et al., 2010). For firms, this poses the question of how to fight NWOM in OSN efficiently. While He et al. (2012) and Mochalova and Nanopoulos (2014) develop efficient seeding strategies on how to select people in OSN for spreading the counter message, Beşer et al. (2016) analyse the roles of the number of seeds, the delay between NWOM and PWOM, and the informational quality of the counter message. This paper is mostly related to the paper of Beşer et al. (2016). In contrast to the abovementioned papers that develop efficient algorithms to choose an optimal set of seeds, this paper, like Beşer et al. (2016), focuses on the nature of the message, i.e. the informational quality determined by its emotional and rational dimension (Sweeney et al., 2012; Allsop et al., 2007) and how to react to NWOM. We also do not explicitly choose seeds in the network but assume that firms have some network participants to their disposal that can be activated in case of an online firestorm (see the according discussion in Beşer et al., 2016). Like in Beşer et al. (2016) and Trpevski et al. (2010), we allow people to switch between believing NWOM and PWOM as long as they receive messages. But in contrast to these two papers, we introduce a range of indifference in cases where both messages are credible but too similar in terms of persuasiveness. All the other papers consider a so-called progressive spread (Kempe et al. 2003) where network participants cannot change their opinion once they are convinced of one message. As in Beşer et al. (2016) and Mochalova and Nanopoulos (2014), we consider a time delay between the initial message and the counter message. Except for Chen et al. (2011), who study the situation that the quality of a product turns people to spread a positive experience with probability $\alpha$ and a negative experience with $(1-\alpha)$, this paper considers in contrast to all the aforementioned papers that a message can trigger the opposing message if both messages were received by a network participant. This depicts the situation when a firm issues a statement regarding NWOM after a certain amount of time making people upset. Then, the negative message spreads again and reduces the effect of the PWOM campaign. In addition, this paper is the only one in the context of competitive WOM that provides an economic valuation of possible countermasures against NWOM. Usually, the economic consequences of fighting NWOM are not explicitly taken into account.

3 Model

3.1 Network Model

A social network can be seen as an undirected graph $G=(V,E,B)$ with $V$ being a finite set of nodes denoting network participants, $E$ being a finite set of edges representing social relationships between nodes, and $B$ being a function that assigns a weight $b_{ij}$ to an edge $(i,j) \in E$: $B:E \rightarrow [0,1]$. Two nodes $i,j \in V$ are adjacent to each other if there is an edge $(i,j) \in E$ where $i \neq j$. The neighbourhood of $i$ can be described as $N_i = \{ j \in V : (i,j) \in E \}$. The weighting $b_{ij} \in [0,1]$ attached to each edge represents the intenseness of the social relationship between $i$ and $j$. Values close to 0 indicate a weak-tie relationship, whereas values close to 1 represent a strong-tie relationship (Granovetter 1973). However, even though the network is considered as an undirected graph, the tie strength between two participants $i$ and $j$ may not be reciprocally equal so that in general $b_{ij} \neq b_{ji}$. 


The network supports two different messages of opposite valence, namely the NWOM and PWOM message. If a network participant i receives a message at time step t, he will evaluate its credibility depending on its characteristics and the behaviour of his peers. With more of his contacts being convinced of the message, the probability of i also believing in the message increases. These two factors combined must exceed i’s personal threshold in order to convince him of the message’s truthfulness. If i has received the opposing message until the time step considered, he will compare both messages and decide for the more convincing one. If the messages are too similar in terms of threshold exceedance, he will change to an indecisive state. But he will never believe in both messages at the same time. If i receives the opposing message at a later time step, he will re-evaluate both messages and reconsider his formerly made decision.

3.2 Credibility of a Message

Our model is mainly based on the diffusion model presented by Beşer et al. (2016) that is premised on the dual-process theory of Deutsch and Gerard (1955). There, the credibility of a message depends on two types of interpersonal influence: normative social influence (NSI) and informational social influence (ISI). ISI represents the content of messages sent in OSN (Cheung et al., 2009) and describes the tendency of human beings to accept information transmitted by others as a proof of facts. NSI equates to the natural predisposition of individuals to conform to the behavioural expectations of their peer group (Hsu and Tran, 2013; Van Eck et al., 2011; Cheung et al., 2009). It represents the social pressure that occurs during opinion exchange when a consensus is formed within the personal network Ni of a network participant i (Cheung et al., 2009; Van Eck et al., 2011).

To which extend ISI and NSI influence the individual credibility perception depends on the considered market (Batra et al., 2001). It is conceivable that in turbulent markets such as fashion markets people pay more attention to the behaviour of their peers (i.e. NSI) and less on the content of a message (i.e. ISI) when making a decision (Delre et al., 2007). With a weighting factor $\beta \in [0,1]$ the turbulence of a market can be adjusted. Markets where NSI is higher weighted ($\beta \rightarrow 1$) are called collectivistic markets and markets where ISI is more valued ($\beta \rightarrow 0$) individualistic markets. Since $\beta$ is an estimated value lacking empirical data, we vary $\beta$ around it. To analyse the effectiveness of a countermeasure against a negative message, the model also needs to differentiate between negative and positive messages. For this let $m \in \{+,-\}$ denote the valence of a message and $\bar{m} \in \{+,-\}\backslash m$ the valence of the opposing message. The valence indicates if the message is a PWOM ($m = +$) or NWOM ($m = -$) message. Let $t \in [1,T]$ indicate the current time step. In line with Beşer et al. (2016), the credibility $C_i^m$ of a message $m$ perceived by a network participant i at time step t is described as:

$$C_i^m = \beta_i \cdot \text{NSI}_i^m + (1 - \beta_i) \cdot \text{ISI}_i^m,$$

(1)

If $C_i^m$ surpasses a certain threshold $\Phi_i^m \in [0,1]$, recipient i will believe message m. Due to the so-called negativity bias, people tend to perceive negative messages as more informative and useful (Cannarella and Piccioni, 2008; Sen and Lerman, 2007; Skowronski and Carlston, 1989). A possible explanation for this is that good quality can be attributed to both good and bad products whereas bad quality is only attributable to the latter (Lee et al., 2008). Various findings indicate that NWOM messages are twice as powerful as PWOM messages (Amini et al., 2012; Goldenberg et al., 2007; Sweeney et al., 2005). Therefore, the threshold for PWOM is double the threshold of NWOM $\Phi_i^+ = 2 \cdot \Phi_i^-$, leading to NWOM messages being more easily believed by network participants.

If a recipient has received both the NWOM and PWOM message, a separate comparison of the credibilities with the individual thresholds is not feasible anymore because both thresholds can be surpassed at the same time. Due to the asymmetry in the threshold levels, the exceedances have to be compared in relative terms. For this, let $TE_i^m = (C_i^m - \Phi_i^m)/(1 - \Phi_i^m) \forall C_i^m \geq \Phi_i^m$ with $TE_i^m \in [0,1]$ denote the threshold exceedance of a message m. If the threshold exceedance of message $\bar{m}$ is greater than the one of
m, recipient i will favour message m over \( m \). But this only holds if the difference between the threshold exceedances \( T_{E_{i}} \) and \( T_{E_{i_{m}}} \) is great enough. If the difference is too small, recipient i will most probably stay indecisive. In contrast to Beşer et al. (2016), we therefore introduce a range of indifference \( \vartheta \). Only if the difference between \( T_{E_{i}} \) and \( T_{E_{i_{m}}} \) is greater than or equal to this range of indifference, recipient i will believe the stronger message. The higher \( \vartheta \) is, the greater the difference between \( T_{E_{i}} \) and \( T_{E_{i_{m}}} \) has to be in order to make the recipient believe the stronger message. Hence, a higher \( \vartheta \) resembles situations where network participants act more cautiously and believe neither message if they are too similar in terms of threshold exceedance. As a result, the decision \( c_{it}^{m} \) of a network participant i regarding the message m at time step t is calculated as follows:

\[
c_{it}^{m} = \begin{cases} 
1 & \text{if } C_{it}^{m} \geq \Phi_{i}^{m} \land C_{i_{m}}^{m} < \Phi_{i_{m}}^{m} \land \text{TE}_{i_{m}} > \text{TE}_{i} \land |\text{TE}^{m}_{i_{m}} - \text{TE}^{m}_{i}| \geq \vartheta, \\
1 & \text{if } C_{it}^{m} \leq \Phi_{i}^{m} \land C_{i_{m}}^{m} \geq \Phi_{i_{m}}^{m} \land \text{TE}_{i_{m}} > \text{TE}_{i} \land |\text{TE}^{m}_{i_{m}} - \text{TE}^{m}_{i}| \geq \vartheta, \\
0 & \text{else}
\end{cases}
\]

Hereby, the binary decision variables \( c_{it}^{m} \) indicate if i believes the PWOM (\( c_{it}^{m} = 1 \land c_{i_{m}}^{m} = 0 \)) or the NWOM (\( c_{it}^{m} = 0 \land c_{i_{m}}^{m} = 1 \)) message at time step t. Note that by definition \( c_{it}^{m} \) and \( c_{i_{m}}^{m} \) cannot be 1 at the same time. Based on these variables, the spread \( S_{it}^{m} \) of the message m in the network at time step t can be calculated as (Beşer et al., 2016):

\[
S_{it}^{m} = \frac{1}{|V|} \sum_{i \in V} c_{it}^{m}
\]

### 3.3 Normative Social Influence

NSI reflects the share of a network participant i’s contacts \( N_{i} \) that have forwarded the message to him. The intenseness of the social relationship between recipient i and sender j denoted by \( b_{ij} \in [0,1] \) plays an essential role. With increasing tie strength (\( b_{ij} \rightarrow 1 \), i is more inclined to believe the information sent by j (Ryu and Han, 2009). Let \( FD_{ij}^{m} \in \{0,1\} \) denote if i’s contact j has forwarded message m to i at time step t. Then the social pressure \( P_{it}^{m} \) perceived by i regarding the message m at time step t is calculated as (Beşer et al., 2016):

\[
P_{it}^{m} = \sum_{j \in N_{i}} b_{ij} \sum_{j \in N_{i}} FD_{ij}^{m} \]

It is conceivable that already a small number of peers can exert relatively high pressure on participant i. Hence, we assume that after reaching a certain level of saturation any more peers will hardly add to the perceived social pressure. With the help of the logistic function (LF), the pressure \( P_{it}^{m} \) can undergo a transformation in order to achieve such an effect. Since \( NSI_{it}^{m} \) should only be calculated if the according message m is received, let \( r_{it}^{m} \in \{0,1\} \) indicate if i has received the message m until time step t (Beşer et al., 2016):

\[
NSI_{it}^{m} = r_{it}^{m} \cdot LF(P_{it}^{m}) \quad \text{with } LF(x) = \frac{1}{1 + e^{-\beta(x-m)}}
\]

### 3.4 Informational Social Influence

ISI represents the content of a message which consists of a rational and emotional dimension (Sweeney et al., 2012; Allsop et al., 2007). The former refers to the persuasive power of the arguments used in the message (Cheung and Thadani, 2012; Cheung et al., 2008) which constitutes the message’s
argument quality (AQ). AQ has a significant impact on the adoption behaviour of messages (Cheung et al., 2012; Cheung et al., 2008; Zhang and Watts, 2003). The emotional dimension, on the other hand, describes the degree of (dis-)satisfaction that a message sender wishes to express. The more (dis-)satisfied the sender is, the more (negative) positive is the expressiveness (EX) he uses in his message (Buttle, 1998).

The evaluation of a message’s content depends on the characteristics of its sender and recipient. The expertise and social prestige of the sender together with his tie strength to the recipient increase the credibility of the transmitted information (Fan and Miao, 2012; Cannarella and Piccioni, 2008; Brown et al., 2007). On the receiving side, a high expertise enables the recipient to process information that require deeper knowledge about the topic, whereas a low expertise leads to the processing of more easily understandable utility-based information (Sohn, 2014; Park and Kim, 2008). This means that with lower expertise the recipient pays more attention to the expressiveness when evaluating a message. In addition, the expressiveness plays a more important role to the recipient if he is of the same opinion that is expressed in the message (East et al., 2008). Due to the lack of empirical evidence regarding the distribution of these factors, we use like Beşer et al. (2016) a weighting factor $\gamma_i \in [0,1]$ that shall comprise the mentioned characteristics. With the help of $\gamma_i$ and the abovementioned binary variable $r^m_{it}$ the informational social influence $ISI^m_i$ regarding message $m$ perceived by participant $i$ at time step $t$ can be expressed as a linear combination of $AQ^m_i$ and $EX^m_i$:

$$ISI^m_i = r^m_{it} \cdot (\gamma_i \cdot AQ^m_i + (1 - \gamma_i) \cdot EX^m_i), \quad AQ^m_i, EX^m_i \in [0,1] \tag{6}$$

### 3.5 Forwarding Intention, Forwarding Probability, and Forwarding Decision

After receiving a message at time step $t$ and forming a decision about its credibility, recipient $i$ will decide whether or not to forward the message to his neighbours $j \in iN$. Beside the credibility $C^m_{it}$ of a message (Hsu and Tran, 2013), the tie strength between sender and recipient plays an important role for this decision. People tend to exchange information more often with contacts to whom they have a closer relationship (Davis and Khazanchi, 2008; Chiu et al., 2006; Wirtz and Chew, 2002). The interplay of credibility and tie strength for the forwarding intention is complex. They are neither complete antipodes nor do they act fully complementary. On the one hand, a message with low credibility is not forwarded even if there is a strong-tie relationship between sender and recipient because messages with little or no value may harm a social relationship (Sohn, 2014) or the reputation of the sender (Pescher et al., 2013). On the other hand, if the credibility is very high, a message may be forwarded irrespective of the perceived value. Then, even a low tie strength will increase the probability of forwarding instead of lowering it so that credibility and tie strength act additively. Therefore, as in Beşer et al. (2016), we use a parameter $\eta \in [0,1]$ for counter-balancing both factors instead of using a pure linear combination. Moreover, the forwarding intention $FI^m_{it}$ of participant $i$ for sending message $m$ to his peer $j$ is only calculated if $i$ has received the corresponding message $m$ until time step $t$:

$$FI^m_{it} = r^m_{it} \cdot (\eta \cdot b_{ij} \cdot C^m_{it} + (1 - \eta) \cdot (b_{ij} + C^m_{it} - b_{ij} \cdot C^m_{it})) \tag{7}$$

Messages need to be topical to be forwarded, i.e. older messages are less likely to be sent to one’s peers (Falkinger, 2007). As the forwarding frequency of messages in OSN follows an exponential distribution (Nugroho et al., 2015), a global aging factor (AF) is used to lower the forwarding intention $FI^m_{it}$ of message $m$ with increasing time exponentially: $AF^m = \exp(-\ln(2) \cdot (T^m_{1/2} - (t - T^m))) \forall t \geq T^m$ where $T^m$ is the time step at which message $m$ initially shows up in the network and $T^m_{1/2}$ denotes its half-life, i.e. after how many time steps message $m$ loses half of its topicality. Sometimes a reaction to NWOM can trigger a new wave of negative information spread throughout the network (Van Noort and Willemsen, 2012). In contrast to other papers (see section 2), we want to consider this effect in our
analysis so that a rejuvenation of the first message’s topicality is needed. Once recipient i has received both messages, the superordinate topic of both messages’ content gains topicality for i. Therefore, he forwards a message with the aging factor of the younger message as soon as he has received it:

\[
FP_{ij}^m = \begin{cases} 
  F_{ij}^m \cdot (r_i^m \cdot AF_i^m + (1-r_i^m) \cdot AF_r^m) & \text{if } T_m \geq T^m \\
  F_{ij}^m \cdot AF_r^m & \text{else}
\end{cases}
\]

(8)

Network participant i forwards message m to his contact j at time step t+1 only if \( FP_{ij}^m \) exceeds a uniformly distributed random variable \( u_{ij} \in [0,1] \) that is individually generated for every contact \( j \in N_i \) at each time step t. A prerequisite for this is that i has not forwarded message m to j at an earlier time step \( t' < t \). Because people communicate with others in order to promote or maintain their reputation (Lampel and Bhalla, 2007), sending the message twice to the same person would harm the sender’s status. In addition, i must have received at least one of the two messages (i.e. the NWOM and/or PWOM message) at time step t. Furthermore, message m should only be forwarded if network participant i believes in the message or is indecisive, but not if he is convinced of the opposing message (i.e. \( c_i^m = 0 \)). As a result, the forwarding decision \( FD_{ij}^m \) of i to contact \( j \in N_i \) at time step t+1 is calculated as follows:

\[
FD_{ij}^m = \begin{cases} 
  1 & \text{if } FP_{ij}^m \geq u_{ij} \wedge \sum_{t=1}^{T} FD_{ij}^m = 0 \wedge \sum_{n \in \{1, \ldots, k\} \in N_i} FD_{in}^m \geq 1 \wedge c_i^m = 0, \quad t \in [T^m, \infty) \\
  0 & \text{else}
\end{cases}
\]

(9)

The operationalisation of \( r_{it}^m \) is based on the forwarding decision and indicates if i has received message m until time step t+1. This may be the case if at least one of his contacts has sent him the message or if he is activated as a seed at time step t.

\[
r_{it}^m = \begin{cases} 
  1 & \text{if } \sum_{j \in N_i}^{T} FD_{ij}^m \geq 1 \wedge r_{it}^m = 1, \quad t \in [T^m, \infty) \\
  0 & \text{else}
\end{cases}
\]

(10)

### 3.6 Purchase Intention and Purchase Decision

If a network participant i believes a message, it might increase or decrease his purchase intention depending on the message’s valence (Akyüz, 2013; Cheung and Thadani, 2012; Fan and Miao, 2012; East et al., 2008). According to the prospect theory of Kahneman and Tversky (1979), people place possible gains and losses in relation to a reference point when making a decision under risk. In such situations, the behaviour of people is characterised by loss aversion. That means that an NWOM message decreases the purchase intention more than a PWOM message of the same intensity can increase it (Lee et al., 2008). Let \( PP_i \in [0,1] \) be the purchase probability denoting the individual reference point. Then, the purchase intention \( PI_i \) of network participant i at time step t can be described as a function of the perceived message credibility \( c_i^m \) and his decision \( c_i^m \).

\[
PI_i = \begin{cases} 
  PP_i + (PI_{i,\text{max}} - PP_i) \cdot (1 - e^{-c_i^m}) & \text{if } c_i^m = 1 \\
  PP_i - (PP_i - PI_{i,\text{min}}) \cdot (1 - e^{-c_i^m}) & \text{if } c_i^m = 1, \quad PI_{i,\text{min}} \in [0,PP_i], PI_{i,\text{max}} \in [PP_i,1]
\end{cases}
\]

(11)

By introducing upper and lower bounds (\( PI_{i,\text{max}} \) and \( PI_{i,\text{min}} \)) the model’s adaptability to the asymmetry substantiated by the prospect theory is ensured. An exponential increasing/decreasing of the purchase
intention has been chosen because the theory’s value function is usually concave above the reference point and in most cases convex below it (Barberis, 2013; Kahneman and Tversky, 1979). If the purchase intention exceeds a uniformly distributed random variable \( u_i \in [0,1] \), the purchase decision \( PD_i \) of network participant \( i \) will be positive at time step \( t \) (i.e. \( PD_i = 1 \)) and negative in the other case (i.e. \( PD_i = 0 \)). With the help of \( PD_i \) the share of the network participants \( B_i \) who would potentially buy the product at time step \( t \) can be calculated as follows:

\[
PD_i = \begin{cases} 
1 & \text{if } PI_i \geq u_i \\
0 & \text{else}
\end{cases}
\]

(12)

\[
B_i = \frac{1}{|V|} \sum_{i \in V} PD_i
\]

(13)

4 Numerical Analysis

4.1 Parameterisation

Granovetter (1973) provided a first conceptualisation of complex social networks. He postulated that social networks mainly consist of two components: Highly clustered sub-networks where members intensively communicate with each other and so-called bridges or short cuts that interconnect these networks and ensure a fast diffusion of information (Cowan and Jonard, 2003; Watts and Strogatz, 1998). Onnela et al. (2007) found empirical evidence for this theory by analysing usage data of 4.6 million mobile phone users. For our experiments, we used the small world network graph model developed by Watts and Strogatz (1998) that shares both of these characteristics. To obtain sufficiently representative values, 500 simulation runs were executed for each conducted parameter variation. For each run, a new small world network was generated with \( n = 1000 \) nodes, a lattice parameter of \( k = 6 \), and a rewiring probability of \( s = 0.1 \). Then, the generated networks usually had an average path length of \( APL \approx 6.3 \) and a global clustering coefficient of \( GCC \approx 0.43 \). The latter represents a measurement for the network connectedness summed up over all local sub-networks and the former measures the speed of diffusion within the whole network (Watts and Strogatz, 1998). Real social networks are found to provide similar values for \( APL \) (Milgram, 1967).

The remaining parameter settings that are fixed during simulation runs are as follows: The expected value \( (\mu) \) and standard deviations \( (\sigma) \) for generating the message credibility thresholds from a truncated normal distribution within the interval \([0,1]\) are \( \mu(\Phi^r) = 0.5 \), \( \mu(\Phi^s) = 0.25 \), \( \sigma(\Phi^r) = 0.125 \), and \( \sigma(\Phi^s) = 0.0625 \). The weighting parameters between \( NSI_i^m \) and \( ISI_i^m \) as well as \( AQ_i^n \) and \( EX_i^n \) are likewise generated from a truncated normal distribution. The corresponding values are \( \mu(\beta_i) = \beta \), \( \sigma(\beta_i) = 0.125 \), \( \mu(\gamma_i) = 0.5 \), and \( \sigma(\gamma_i) = 0.125 \). Because there is a lack of empirical evidence how tie strength and perceived message credibility influence each other, the counter-balancing factor for the forwarding intention is set to \( \eta = 0.5 \). This depicts the basic case where no counter-balancing occurs between the two parameters. For the logistic function to generate \( NSI_i^m \), we use \( \delta = 20 \) for its steepness and \( \omega = 0.25 \) for the sigmoid’s midpoint. With this parameterisation, \( NSI_i^m \) rises quickly enough with growing social pressure \( P_S^m \) to reach values close to 1 for \( P_S^m \geq 0.5 \). Like in Beşer et al. (2016), the half-life of both messages is set to \( T_{1/2}^m = 10 \). The range of indifference is set to \( \Theta = 0.1 \). A rather small value was chosen because at higher values consumers will tend to stay indecisive when they have received both messages. This would impede an adequate examination of the messages’ impact. As additional experimental results show (not presented in the following), this applies in particular to cases where both the NWOM and PWOM message have a high spread. The purchase probability of all network participants is fixed at \( P_P = 0.1 \), meaning that 10% would buy the product in the first place. We have conducted the following experiments for other values of the purchase probability and found no significant differences in the simulation outcomes. The values for the share of buyers were scaled.
by the purchase probability but the relations between different settings remained the same. The parameters for exponentially increasing or decreasing the purchase intention are \( \lambda^+ = 5 \) and \( \lambda^- = 2.5 \). The boundaries to limit the changes of the purchase intention evoked by the messages are \( P_{l_{\text{max}}} = 0.125 \) and \( P_{l_{\text{min}}} = 0.05 \).

### 4.2 Non-Competitive Setting: NWOM Spread Without Countermeasure

To analyse the efficiency of different strategies, first the NWOM spread without the existence of any measures has to be determined. For this, we varied the argument quality \( \text{AQ}^- \) and expressiveness \( \text{EX}^- \) of an NWOM message in equal steps for different markets. Figure 1 shows the final NWOM spread \( S_T \) and share of buyers \( B_i \) for different values of \( \text{AQ}^- \) and \( \text{EX}^- \) where \( T \) denotes the time step at which the simulation ended, i.e. when all network participants stopped forwarding messages to their peers: \( T = \max\{t \in \{1, \ldots, T\} : \sum_{j=1}^{N} \sum_{i=1}^{n} F_{D_j} \geq 1\} \). Note that due to the lack of empirical data \( \mu(\gamma) = 0.5 \) was chosen. That means that \( \text{AQ}^- \) and \( \text{EX}^- \) are treated as being equally important to the recipient. This in turn leads to \( \text{AQ}^- \) and \( \text{EX}^- \) being interchangeable in the given case, meaning that on average \( \text{AQ}^- = \text{EX}^- \) has the same effect as \( \text{AQ}^- = \text{y} \) \( \text{EX}^- = \text{x} \). Therefore, in each experiment both factors were assigned the same value: \( \text{AQ}^- = \text{EX}^- = \text{x} \) with \( \text{x} \in \{0.1, 0.2, \ldots, 1\} \).

![Figure 1. NWOM spread and share of buyers for different values of AQ- and EX-.](image)

As Figure 1a shows, the NWOM spread is much higher in individualistic markets. This particularly applies to stronger NWOM messages. The more collectivistic a market is (\( \beta \rightarrow 1 \)), the lower the NWOM spread gets leading to a hardly distinguishable overlapping of the graphs for the most collectivistic markets. This can be explained by the fact that in individualistic markets the message content (i.e. ISI\( m \) consisting of \( \text{AQ}^m \) and \( \text{EX}^m \)) is more valued in the credibility evaluation than the peer behaviour (i.e. NSI\( m \)). Since the perceived credibility of a message also plays an important role in the forwarding decision of network participants, more credible messages spread further. This is only valid to a limited extent for collectivistic markets where the credibility is for the most part based on the sending behaviour of a network participant \( i \)'s contacts. If they do not send the message, \( i \) will most probably not forward the message either so that the propagation of the message in the network is reduced. Figure 1b shows that the NWOM spread is negatively correlated with the share of buyers. In the most individualistic market (\( \beta = 0 \)) the number of potential buyers is reduced by the strongest NWOM Message by approximately 40% in relative terms. As \( \beta \) increases, all NWOM messages lose their negative effect on the purchase intention. In the following, we pick a weak (\( \text{AQ}^- = \text{EX}^- = 0.3 \)), medium (\( \text{AQ}^- = \text{EX}^- = 0.6 \)), and strong (\( \text{AQ}^- = \text{EX}^- = 1 \)) NWOM message for further examination.

### 4.3 Competitive Setting: Quick-Response Countermeasure

In the competitive setting, a firm reacts with a PWOM message to NWOM. To analyse the countermeasure efficiency, a weak (\( \text{AQ}^- = \text{EX}^- = 0.3 \)), medium (\( \text{AQ}^- = \text{EX}^- = 0.6 \)), and strong (\( \text{AQ}^- = \text{EX}^- = 1 \)) PWOM message were chosen to be either launched by one or eight seeds. The graphs in Figure 2a/b/c show that in most cases a significant reduction of the NWOM spread is only achieved if a strong
PWOM message is used. If the strong PWOM message is launched by one seed against a weak or medium NWOM message, it is not only able to repair the damage of the NWOM message but can also increase the share of buyers in almost all markets above the initial share of 10% (2d/e). Only in the case of a strong NWOM message, multiple seeds are needed to fully reverse the financial damage caused by the NWOM message (2f). Using eight seeds instead of one increases the reducing effect of the strong PWOM message in all cases and leads to a higher share of buyers. However, the effects of more seeds are considerably lessened for the weak and medium PWOM messages. Furthermore, it is noticeable that the weak NWOM message has a very low spread in all markets (2a) and hardly reduces the share of buyers (2d) making a reaction unnecessary.

Another important finding is that a strong PWOM message with one seed usually outperforms a weak or medium message launched by eight seeds. This is particularly true if individualistic markets are considered. The greatest difference can be observed for a strong NWOM message (2c) in the most individualistic market ($\beta=0$) where the strong PWOM message with one seed outperforms the medium message with eight seeds by more than 50% ($S_r = 30.73\%$ vs. $S_r = 88.18\%$). With increasing $\beta$ the difference starts to vanish and in the most collectivistic markets the strong PWOM message forfeits its advantage over the medium and weak message with eight seeds. The reason is that peer behaviour is higher valued in these markets which gives the countermeasure with multiple seeds an advantage over the single-seed strategy.

4.4 Competitive Setting: Delayed Countermeasure

Now, the PWOM message is not launched immediately but after a reaction time of $T^S = T^- T^- = 8$ time steps. In this case, a strong PWOM message with one seed (3a/b/c) reduces the NWOM spread in individualistic markets more than any immediately launched weak or medium PWOM message with one seed (2a/b/c). The greatest difference can be observed in the most individualistic market ($\beta=0$) for the medium NWOM message. There, the delayed strong PWOM message (3b) reduces the NWOM spread with one seed ($S_r = 3.01\%$) significantly more than the medium PWOM message (2b) launched immediately with one seed ($S_r = 21.27\%$). Even if the medium PWOM message is launched by multiple seeds, it is still inferior ($S_r = 22.59\%$). The superiority of a delayed strong PWOM message
launched by one seed over instantaneously launched weaker PWOM messages with multiple seeds occurs in the other NWOM cases, too. Figure 3c shows for example that in the most individualistic market ($\beta = 0$) the delayed strong PWOM message with one seed is able to outperform the medium PWOM message that is launched immediately with eight seeds (2c) by 20% ($S_7 = 68.18\%$ vs. $S_7 = 88.18\%$). Similar results can be observed for the share of buyers. In the cases of a weak and medium NWOM message (3d/e), the delayed strong PWOM message with one seed outperforms the weaker counter messages with eight seeds (2d/e) for $\beta < 0.4$. In case of a strong NWOM message (3f), the delayed PWOM message is also superior for $\beta < 0.4$.

Interestingly, the reaction to NWOM can be counterproductive. As Figure 3 reveals, in some situations a delayed reaction with multiple seeds leads to a growth in the NWOM spread and possibly to a decline in sales compared to the case when no countermeasure is taken at all. In case of a weak NWOM message for example (3a) the triggering caused by the weak PWOM message with eight seeds increases the NWOM spread in all markets. This is also valid for the medium PWOM message except for individualistic markets ($\beta < 0.3$). In contrast, the strong PWOM message is mostly able to decrease the NWOM spread except for very collectivistic markets ($\beta > 0.7$). But, as shown in Figure 3d, this triggering of NWOM does not necessarily result in an additionally decreased number of buyers. A similar increase of the NWOM spread can be observed in the case of the medium NWOM message fought by weak and medium PWOM messages (3b). However, in this case (3e), the weak PWOM message makes the sales decline in individualistic markets ($\beta < 0.4$). If a strong NWOM message is countered, the NWOM spread is again increased for the weak and medium PWOM message (3c). But contrary to the other NWOM cases its growth mostly leads to an additional decrease in the number of buyers (3f). Only the strong PWOM message is able to compensate the impact of NWOM to some extent and to generate additional sales which mainly occurs in very collectivistic markets ($\beta > 0.6$). All this means that only those PWOM messages that are at least as strong as the NWOM message have a noticeable positive effect on sales. If the PWOM message is weaker than the NWOM message, it usually harms the sales.

Now the question is why do the triggering and the associated decline in sales not occur when the quick-response countermeasure is taken with eight seeds? An explanation for this is that a delayed

![Figure 3](image-url)
PWOM message ($T^8 = 8$) is confronted with a negatively prepared market and therefore faces greater difficulties in establishing itself in the network. Because of this, less people forward the PWOM message and the PWOM spread is comparatively low. But at the same time the PWOM message is responsible for the initiation of a new wave of NWOM messages. This happens to be more intense if eight seeds are used instead of one. If a firm reacts immediately ($T^8 = 0$) with eight seeds, the situation is different. Then, the PWOM message has better chances in fighting NWOM because large parts of the network have not been taken by the NWOM message yet. Network participants will forward the PWOM message more often and the PWOM spread will be higher leading to fewer people believing the NWOM message. This explanatory approach is evidenced by the NWOM spread that is generally lower for the quick-response countermeasure shown in Figure 2 compared to the delayed reaction depicted in Figure 3.

The degree to which a market is negatively prepared is an important aspect that must not be neglected in the context of a delayed reaction. The weaker an NWOM message is, the more likely is the delayed PWOM message to propagate and vice versa. Our results show that the PWOM spread is in fact higher for the weak and medium NWOM messages (not depicted). The higher PWOM spread in turn leads to NWOM being more often triggered which explains the increased NWOM spreads in Figure 3a/b/c. This also explains why the increased NWOM spreads lead to fewer sales in the case of a strong NWOM message (3f), but not in the cases of weak and medium NWOM messages (3d/e). In the latter cases there is no dominating message that might extensively restrict the other message from spreading. Therefore, the weak and medium PWOM messages get forwarded more often when they are facing weak or medium NWOM messages. While this leads to an increased NWOM spread, it also means that more people will believe in the PWOM message as well. Its advertising impact on the network participants will ultimately result in more people buying the product. From this it may be inferred that the spread of a PWOM message has two opposing effects on the NWOM spread and share of buyers. Firstly, it may trigger a new wave of NWOM messages and thereby increase the NWOM spread and decrease the number of sales. Secondly, by reaching a greater spread itself and inducing sales-promotional effects the PWOM message may reduce or even reverse the negative effects caused by the higher spread of the NWOM message. However, in the case of a strong NWOM message its overwhelming strength prevents the PWOM messages from reaching a high spread (not depicted). Therefore, the second effect can hardly compensate for the former resulting in an additional decline in sales as shown in Figure 3f.

5 Discussion

The aim of this paper was to analyse and evaluate different strategies for fighting NWOM. For this, we extended the diffusion model of Beşer et al. (2016) by introducing a range of indifference and a triggering of older messages by newer ones. This triggering may usually happen if firms try to counter NWOM with a PWOM message. By analysing the quick-response countermeasure we found that in most cases a significant reduction is only achieved if a strong PWOM message is used. Otherwise the reduction effects are too small, even if multiple seeds are used. Thus, we can conclude that it is more profitable to react with one seed and a strong PWOM message than launching a badly designed message with more seeds. This also holds true if the strong PWOM message is launched with delay. A well-designed counter message launched by one seed with delay performs often better than an immediately launched weaker message. This is to some extent also valid if more seeds are used for the weaker message. These findings are in line with Beşer et al. (2016) but contrary to the findings of Mochalova and Nanopoulos (2014) who stated that a quick reaction should be preferred. From an economic point of view, our results show that a rather badly designed delayed PWOM message launched by multiple seeds may be counterproductive in terms of increasing the NWOM spread and decreasing the share of buyers. The later initiated PWOM message has two opposing effects: An increased NWOM spread that limits sales on the one hand, and an advertising effect that attracts new customers.
But the latter can only compensate for the former if the positive message is at least as strong as the negative one.

As a result, several managerial implications can be deduced. First of all, our results show in line with Beşer et al. (2016) that it is advantageous for firms to invest time in a well-designed counter message instead of reacting to NWOM messages as quickly as possible or by using more seeds. Secondly, the activation of multiple seeds should be considered thoroughly. If a firm responds to the negative message inadequately with a weak counter message, using multiple seeds will hardly increase its effect. On the contrary, a badly designed PWOM message may even worsen the situation if it is launched by multiple seeds and with delay. Because then it will trigger a new wave of negative messages increasing the initial NWOM spread. If the PWOM message is not at least as strong as the NWOM message, the triggering might additionally harm the sales. In these cases firms should remain silent if they are not able, for whatever reason, to respond with a well-developed counter message. If a strong NWOM message is being faced, it is inevitable to use more seeds for the strong PWOM message to fully reverse the caused economical damage. In most other cases, using multiple seeds is not necessary but beneficial if a convincing, strong message is used. Thirdly, as already pointed out, a reaction to NWOM is not always mandatory. Weak NWOM messages hardly affect sales so that a firm can save costs by taking no measure. When medium NWOM messages are being countered, firms should remain silent if their reaction was not well received by OSN members. Even if the initial NWOM spread is increased, it will not result in additional losses. A secondary, not well-designed statement of the firm might worsen the situation and lead to financial loss eventually. However, a secondary reaction that should be treated as a third message in the network requiring an extension of the presented model was not part of this study.

There are some limitations of this study that need to be considered. First of all, we made assumptions about some parameters for which empirical data has to be derived. One example is the individual weighting factor $\gamma_i$ between the argument quality and expressiveness of a message. We have chosen $\mu(\gamma_i) = 0.5$ making both factors perceived as equally important to the recipient. It is conceivable that in reality $\gamma_i$ also depends on the market. In new innovation markets for example, large parts of the target group might have a low expertise about a newly introduced product. In that case, as stated in section 3.4, people pay more attention to utility-based, easily comprehensible information which might result in the expressiveness being higher valued in the credibility perception. Secondly, the model does not consider the forming of determination over time: the longer someone believes something, the more difficult it usually gets to convince him of the opposite. By modelling this, the effects of pro-active measures where the PWOM message starts before the NWOM message could be analysed more realistically. Thirdly, the model does not consider a possible reciprocal relationship between the NWOM and PWOM message regarding their influence on the recipient. It is, for example, conceivable that the argument quality of an NWOM message is lowered by the argument quality used in the PWOM message. But it is likewise conceivable that a PWOM message with incomprehensible or wrongful arguments adds to the NWOM message’s strength. Therefore, empirical tests need to be carried out in order to identify all potential interrelationships between both messages. Fourthly, the new wave of NWOM messages that is triggered by the PWOM message consists of the same NWOM message that was originally disseminated in the network. In reality however, a not well-countered customer concern might provoke a more negative reaction of OSN members resulting in an online firestorm (Mochalova and Nanopoulos, 2014). These are usually emotionally charged and characterised by a lack of well-founded arguments (Pfeffer et al., 2014). This would require the presented model to support modification of messages (i.e. AQ and EX). Fifthly, the size of the networks we used was relatively small compared to the size of real OSN. To gain insights into the behaviour of the model under more realistic conditions, a real-life OSN dataset should be used for conducting the experiments. For example, real OSN are recently found to have smaller values for APL between 4.1 and 5.4 (Zhao et al., 2011). Finally, an empirical research should be carried out regarding the validity of the findings of this study.
References


