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More Fans at Any Cost?
Analyzing the Economic Effects of the Ratio of Fans to Non-Fans in a Customer Portfolio Considering Electronic Word-of-Mouth

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Consumers in Online Social Networks increasingly rely on electronic word-of-mouth (eWOM) when making purchase decisions. Recent research suggests positive effects of the resulting strong exposure of fans to eWOM on cash flows. Consequently, companies follow the popular belief that they should maximize their number of fans by intensively promoting their fan pages. However, even though the sentiment of eWOM on fan pages is prevailingly positive, a sheer maximization of fans in a customer portfolio must be critically reflected: while fans yield higher expected cash flows than non-fans, also the associated risk in terms of these cash flows’ volatility might be considerably higher. Thus, diversifying risk by keeping a share of non-fans – or even increasing it – might be economically reasonable. By drawing on a Portfolio Selection Theory-based model and real-world data, this paper analyzes the ratio of fans to non-fans and its economic effects in customer portfolios.

Keywords: customer portfolio management; electronic word-of-mouth (eWOM); online social networks

1 Introduction

Online Social Networks (OSN) have revolutionized interpersonal communication (Berger, Klier, Klier, & Probst 2014; Heidemann, Klier, & Probst, 2012) and became a significant factor in the marketing communication mix of companies (Albuquerque, Pavlidis, Chatow, Chen, & Jamal, 2012; Faase, Helms, & Spruit, 2011; Rishika, Kumar, Ramkumar, & Bezawada, 2013). This significance results particularly from extensive electronic word-of-mouth (eWOM), which is generated by the rising number of active users in OSN and dispersed with previously unknown reach, intensity, and speed. For instance, solely on Facebook almost 1.5 billion monthly active users as of June 2015 (Facebook, 2015) share 684,478 pieces of content and “like” 34,722 brands or
organizations – every single minute (Tepper, 2012).

(Potential) customers increasingly rely on such eWOM generated by other customers when searching for information about products or services (Chen & Xie, 2008; Moon, Bergey, & Iacobucci, 2010). Therefore, many companies host so-called “fan pages” (Kim, Jeong, & Lee, 2010; Rishika et al., 2013) and incentivize (potential) customers to get connected to their fan pages by becoming so-called “fans”. By doing so, a close link between the fan page and their fans is established (Harris & Dennis, 2011; Poynter, 2008) and eWOM generated on the fan page is automatically pushed into the news feeds of all fans (Debatin, Lovejoy, Horn, & Hughes, 2009; Gallaugher & Ransbotham, 2010). Thus, fans are more likely exposed to eWOM from the fan page than non-fans. Recent studies suggest positive effects of the resulting strong exposure of fans to eWOM on their cash flows (Goh, Heng, & Lin, 2013; Rishika et al., 2013). Consequently, many companies follow the popular belief that they should grow the number of fans to a maximum extent, for instance, by intensively promoting their fan pages (McEleny, 2011; O’Reilly, 2013).

However, the positive effects of a high exposure to eWOM hold only true, if the sentiment is positive. Even though the sentiment of eWOM generated on fan pages is prevailing positive (Rishika et al., 2013; Scholz, Dorner, Landherr, & Probst, 2013), the news feed mechanism of fan pages also accelerates and intensifies the exposure of fans to negative eWOM. The stronger exposure to negative eWOM may consequently lead (on average) to a stronger decrease of the cash flows generated by fans compared to those generated by non-fans, who are not directly exposed to sentiment swings on fan pages (cf. Chevalier & Mayzlin, 2006; Liu, 2006). Hence, fans may not only yield higher expected cash flows (than non-fans), but also the associated risk in terms of these cash
flows’ volatility might be considerably higher. Consequently, a sheer maximization of the share of fans in a customer portfolio must be critically reflected.

Existing approaches demonstrate in general how risks in customer portfolios can be diversified by applying Portfolio Selection Theory (e.g., Buhl & Heinrich, 2008; Sackmann, Kundisch, & Ruch, 2010; Tarasi, Bolton, Hutt, & Walker, 2011). However, none of these approaches has been applied on the research subject at hand before. Following Gregor & Hevner (2013, p. 347), who state “[…] that effective artifacts may exist in related problem areas that may be adapted […] to the new problem context”, this paper therefore aims at bringing together prior work from research on customer portfolio optimization and empirical findings on eWOM to investigate the economic effects of the ratio of fans to non-fans in customer portfolios.

In line with Meredith, Raturi, Amoako-Gyampah, & Kaplan (1989, p. 301), who suggest that “[…] all research investigations involve a continuous, repetitive cycle of description, explanation, and testing (through prediction)”, we structure this paper as follows: first, we provide “[…] a well-documented characterization of the subject of interest” (Meredith et al., 1989, p. 301) by means of description. In the next section, we therefore outline the problem context, discuss empirical findings on the economic effects of eWOM, and provide an overview of research on customer portfolio optimization. In this sense, we aim at contributing to fundamental insights by gathering and structuring preliminary empirical results on the economic effects of eWOM by fans and non-fans. Explanation refers to research deriving generalized frameworks, concepts, or analytical models. We follow Gregor & Hevner (2013, p. 347), who state that adapting existing artifacts “[…] is common in IS, where new technology advances [such as OSN] often require new applications (i.e., to respond to new problems) and a consequent need to test or refine prior ideas”. In the subsequent section, we bring together preliminary findings
from cross-disciplinary research in a novel manner and develop a model for the analysis of the economic effects of the ratio of fans to non-fans in customer portfolios as our core artifact. Afterwards, we demonstrate the validity and utility of our model in a case example based on real-world data of an online retailer as well as publicly available data. We show that eWOM significantly influences the cash flows of fans while non-fans are less affected. Furthermore, we perform a sensitivity analysis to check the robustness of our model and discuss key findings. By these means, we aim at providing a basis for further testing in future research. In line with the ongoing research cycle intended by Meredith et al. (1989), we finally summarize our results and provide an outlook on future research as foundation for model extensions.

2 Background and Related Work

In the following section, we first provide relevant information on the research background and second review related work regarding the economic effects of eWOM generated in OSN. Third, we briefly discuss the state of the art of customer portfolio optimization with respect to our research objective. Finally, we explicate the research gap.

2.1 Research Background: eWOM in the Purchase Decision Process and in Online Social Networks

For decades, research emphasizes that traditional, interpersonal word-of-mouth (WOM) is the most important source of information for purchase decision making (Katz & Lazarsfeld, 1955), being more influential than other, marketer-controlled sources (Buttle, 1998). In today’s increasingly interconnected world, information is no longer only spread interpersonally by WOM but also electronically via the Internet (Dellarocas, 2003; Goh et al., 2013). We define such eWOM in line with Henning-Thurau, Gwinner, Walsh, & Gremler (2004, p. 39) as “[...] any positive or negative statement made by potential,
actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet. Such eWOM can influence all three-stages of the purchase decision process, that is, awareness, interest, and final decision (De Bruyn & Lilien, 2008): Product or service awareness increases as more eWOM is created (e.g., Dhar & Chang, 2009; Godes & Mayzlin, 2004) and distributed (Duan, Gu, & Whinston, 2008). After potential customers have become aware of a product or service, they may become interested in obtaining more information (De Bruyn & Lilien, 2008). As evaluating and comparing products or services is difficult in online shopping, pre-purchase uncertainty about quality and the perceived risk associated with a purchase are high (Gefen, Benbasat, & Pavlou, 2008). Consequently, potential customers usually try to reduce their perceived risk by searching for information beyond product descriptions (Ross & Bettman, 1973; Zhu & Zhang, 2010). Positive eWOM can help to reduce the perceived risk (Dimoka, Hong, & Pavlou, 2012). Negative eWOM, however, produces the reverse effects (e.g., Dellarocas, Zhang, & Awad, 2007; Yin, Bond, & Zhang, 2011).

Whether potential customers finally decide to purchase a product or service depends on the level of perceived attractiveness (Hauser & Wernerfelt, 1990) and again on the perceived risk (Cunningham, Gerlach, Harper, & Young, 2005). Both volume (e.g., Dhar & Chang, 2009) and sentiment (e.g., Chintagunta, Gopinath, & Venkataraman, 2010; Scholz et al., 2013; Sonnier, McAlister, & Rutz, 2011) of eWOM have been shown to affect purchasing decisions.

The influence of eWOM on the purchase decision process is particularly due to two reasons: first, customers consult and trust eWOM more than marketer-generated content (Chen & Xie, 2008; Dellarocas, Awad, & Zhang, 2007; Moon et al., 2010; Narayan, Rao, & Saunders, 2011) and have manifold motives (e.g., ease of use) for seeking opinions online (i.e., eWOM) (Goldsmith & Horowitz, 2006). Second, eWOM is
spread with higher speed, reach, and immediacy than (traditional) WOM before purchase decisions take place (Henning-Thurau et al., 2004; Li & Zhan, 2011).

OSN have even reinforced and accelerated the spread of eWOM (Dellarocas, 2003) by offering a livelier and more direct interaction between (potential) customers and companies, and particularly among customers themselves (Bonchi, Castillo, Gionis, & Jaimes, 2011; Brock, Blut, Linzmajer, & Zimmer, 2011). According to Boyd & Ellison (2013, p. 158), we define an OSN as a “[...] networked communication platform in which participants 1) have uniquely identifiable profiles that consist of user-supplied content, content provided by other users, and/or system-provided data; 2) can publicly articulate connections that can be viewed and traversed by others; and 3) can consume, produce, and/or interact with streams of user-generated content provided by their connections on the site [usually via a so-called news feed]”. While OSN were originally designed for private users (Bughin & Manyika, 2007), they nowadays also attract large numbers of companies that perceive them as a perfect platform for communicating directly with their (potential) customers (Heidemann et al., 2012; Nagle & Pope, 2013). Customers now even expect companies being present in OSN and using them as communication platform such that they became almost inevitable for improving customer relationships and brand perceptions (Dutot, 2013). To do so, companies increasingly launch corporate profile pages, so-called “fan pages” (Kim et al., 2010; Wen, Tan, & Chang, 2009), and create marketer-generated content with the goal of simultaneously promoting their brands and advertising specific products or services (Scholz et al., 2013). To leverage the potential of eWOM, fan pages offer customers the possibility to express their opinions by creating new content or by commenting, liking, or sharing existing content. The fact, that customers actually expose themselves voluntarily to brand information by choosing to become a fan by themselves makes this eWOM on fan pages more influential and
accelerates and facilitates its distribution even more (Chu & Kim, 2011). Because of the push mechanism of fan pages, where content is pushed immediately into the news feeds of fans, on the contrary to non-fans, they are on a regular basis subject to this even more immediate form of eWOM. As not being connected to the fan page, non-fans do not have that direct link and are therefore less or even not at all exposed to company-related eWOM. For non-fans, receiving the same information in the identical intensity would therefore take much more effort and time. Due to the high, potentially positive influence of eWOM on customers and the ability of fan pages to even reinforce this influence on fans, many companies follow the popular belief that they should grow their number of fans to a maximum extent, for instance, by intensively promoting their fan pages (McEleny, 2011; O’Reilly, 2013).

2.2 Economic Effects of eWOM Generated in Online Social Networks

Due to the impact of eWOM on the purchase decision process and its reinforcement by means of OSN (cf. section 2.1), a plethora of research began emphasizing that companies need to consider the economic effects of eWOM generated in OSN, which substantially influence the company value in general and the value of customers in particular (Algesheimer & von Wangenheim, 2006; Hogan, Katherine, & Barak, 2003; Kumar et al., 2010; Nitzan & Libai, 2011; Oestreicher-Singer, Libai, Sivan, Carmi, & Yassin, 2013). What is the reasoning behind the relationship between eWOM, customer values, and the value of companies?

First, it is generally acknowledged in the literature that customer relationships account for a considerable share of the company value in many companies (Gupta, Lehmann, & Stuart, 2004; Kumar, Ramani, & Bohling, 2004). While many ways to measure the value of customers have been suggested (for an overview cf. e.g., Gupta & Zeithaml, 2006), it is predominantly the customer lifetime value – generally defined as
“[… ] the present value of all future profits generated from a customer” (Gupta & Lehmann, 2003, p. 10) – that has become an intensively researched and widely accepted concept (Pepe, 2012).

Second, prior (mainly conceptual) work has emphasized that customer retention and profitability (i.e., the ratio of revenues to costs) are two key components of the customer lifetime value (Stahl, Heitmann, Lehmann, & Neslin, 2012), which can be influenced by eWOM (Algesheimer & von Wangenheim, 2006; Kaske, Kugler, & Smolnik, 2012; Ryals, 2003; Weinberg & Berger, 2011).

Third, empirical research has shown that cash flows and related economic measures (e.g., revenues, sales rank, conversion rates, or profitability) are indeed influenced by both, the volume and sentiment of eWOM generated in OSN. A multitude of existing literature (cf. Table 1) confirms a positive influence of an increased volume of eWOM as well as a positive (negative) influence of eWOM with positive (negative) sentiment on cash flows or related measures (analysis based on both aggregated as well as individual product and customer data).

To leverage the positive effect on cash flows of both, an increased volume of eWOM and eWOM with positive sentiment (cf. Table 1), companies approach and incentivize (potential) customers to get connected to their fan page by becoming fans (Rishika et al., 2013). This opt-in mechanism establishes a close link between the fan page and their fans (Harris & Dennis, 2011; Poynter, 2008), as eWOM generated on the fan page is automatically pushed in real-time into the news feeds of all fans (Debatin et al., 2009; Gallaugher & Ransbotham, 2010). Thus, fans are on average exposed to a higher volume of eWOM than non-fans. Moreover, as the users of OSN engaging on fan pages are usually particularly strong admirers of the respective companies and brands (Muniz & O’Guinn, 2001; Rishika et al., 2013), the sentiment of content produced on fan...
pages is mainly positive (Goh et al., 2013; Rishika et al., 2013; Scholz et al., 2013). Therefore, fans are usually not only exposed to a higher volume of eWOM, but also to eWOM with prevailingly positive sentiment. Taken together, prior research shows that fans are exposed to a higher volume of eWOM with mainly positive sentiment, leading to higher expected per capita cash flows generated by fans than those generated by non-fans (Rishika et al., 2013).

Table 1. Relationship between the volume and sentiment of eWOM and revenues

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Context</th>
<th>Dependent variable</th>
<th>eWOM volume</th>
<th>eWOM sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen, Wu, &amp; Yoon (2004)</td>
<td>Books</td>
<td>Sales rank</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Chevalier &amp; Mayzlin (2006)</td>
<td>Books</td>
<td>Sales rank</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Chintagunta, Gopinath, &amp;</td>
<td>Movies</td>
<td>Revenue</td>
<td>x</td>
<td>+</td>
</tr>
<tr>
<td>Venkataraman (2010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dhar &amp; Chang (2009)</td>
<td>Music</td>
<td>Sales rank</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Duan, Gu, &amp; Whinston (2008)</td>
<td>Movies</td>
<td>Revenue</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Liu (2006)</td>
<td>Movies</td>
<td>Revenue</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Ludwig et al. (2013)</td>
<td>Books</td>
<td>Conv. rate</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Luo (2009)</td>
<td>Airlines</td>
<td>Cash flow</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Moe &amp; Trusov (2011)</td>
<td>Beauty products</td>
<td>Revenue</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Sonnier, McAlistier, &amp; Rutz</td>
<td>Tech. products</td>
<td>Revenue</td>
<td>x</td>
<td>+</td>
</tr>
<tr>
<td>(2011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goh et al. (2013)</td>
<td>Apparel retailer</td>
<td>Revenue</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Rishika et al. (2013)</td>
<td>Wine retailer</td>
<td>Profitability</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Analysis based on aggregated customer/product data, analysis based on customer/product individual data, + positive influence, - negative influence, x no influence/not investigated

However, prior empirical findings indicate that the per capita cash flows generated by fans are also more volatile: first, eWOM generated on fan pages can be negative as well (cf. e.g., Scholz et al., 2013) and according to existing research, eWOM with negative sentiment has a negative effect on cash flows and related economic measures (cf. Table 1). This is due to the fact that, as already stated above, admirers of the companies have strong positive feelings towards the products. But intense positive emotions also allow for extreme lows when being confronted with negative events (Strack, Argyle, & Schwarz et al., 1991), such as negative eWOM. Additionally, a fan
page is one of the main channels for disappointed customers to complain and displeased customers exert much more energy spreading their negative experiences than delighted customers their positive ones (Champoux, Durgee, & McGlynn, 2012). Second, as in the case of eWOM with positive sentiment, the news feed mechanism of fan pages also accelerates and intensifies the exposure of fans to eWOM with negative sentiment. Although negative eWOM generated on fan pages can also be transferred to non-fans by face to face communication or other channels, the cash flows generated by fans on average decrease stronger than those by non-fans, as – due to the news feed mechanism – negative eWOM spreads instantaneously and automatically to all fans (cf. e.g., Chevalier & Mayzlin, 2006; Liu, 2006).

Taken together, based on existing literature, the expected cash flows generated by fans can be assumed to be higher in comparison to non-fans, but they might also be more volatile, which implies a risk for companies. For instance, Dhar & Glazer (2003) as well as Ryals (2002; 2003) point out that when valuating customer portfolios such risks associated with single customers or customer segments need to be considered, that is in our context, the risk in terms of the volatility of the expected per capita cash flows.

2.3 Customer Portfolio Optimization

Analogous to the case of financial portfolios, above mentioned differences in the risk/return structure of single customers or customer segments (here: the segments of fans and non-fans) enable companies to utilize diversification effects. Several existing studies already demonstrate the applicability of Markowitz’s Portfolio Selection Theory (Markowitz, 1952; 1959) in the context of customer portfolio management (Buhl & Heinrich, 2008; Sackmann et al., 2010; Tarasi et al., 2011). Buhl & Heinrich (2008), for instance, differentiate customer segments according to customers’ professions and conclude that imperfect correlations between segments (as given in our case by the
differing exposure of fans and non-fans to eWOM) allow for diversifying risk in customer portfolios. Tarasi et al. (2011) build on these considerations and exploit general customer heterogeneity to improve value creation in customer portfolios. Sackmann et al. (2010) distinguish loyal, relationship-oriented, and transaction-oriented customers and find that individual customer behavior can be better predicted and strategic target group considerations (here: the promotion of fan pages to grow the share of fans in a customer portfolio) are facilitated by their segmentation approach. Ryals, Dias, & Berger (2007) even propose a customer portfolio optimization approach to explicitly support marketing budget allocation decisions. Summing up, several existing studies already demonstrated the applicability of Portfolio Selection Theory in the context of customer portfolio management in order to diversify risks (Buhl & Heinrich, 2008; Sackmann et al., 2010; Tarasi et al., 2011) and to guide the allocation of marketing budgets (Ryals et al., 2007).

2.4 Research Gap

According to the paradigm of value-based management (Coenenberg & Salfeld, 2007), which postulates “[...] the maximization of the long-term sustainable enterprise value as a guideline for all business activities” (Buhl, Röglinger, Stoeckl, & Braunwarth, 2011, p. 164), the popular belief that companies’ marketing efforts should aim at turning a maximum share of their customers to fans must be critically reflected: while fans yield higher expected cash flows than non-fans (cf. e.g., Rishika et al., 2013), also the associated risks in terms of these cash flows’ volatility might be considerably higher. Thus, diversifying this risk by keeping a share of non-fans – or even increasing it – might be economically reasonable. However, to the best of our knowledge, approaches for the optimal allocation of a company’s customers to the segments of fans and non-fans in a value-based manner are missing. Therefore, we suggest a model for the analysis of the economic effect of the ratio of fans to non-fans in a company’s customer portfolio in the
3 Customer Portfolio Optimization Model

Even though the focus of this paper is on the two segments of fans and non-fans, we state the model in a general form, thus making it easy to incorporate more customer segments. This could be applicable in further, consecutive research considering a finer grained segmentation based on further customer characteristics such as age or income level. In line with prior work on customer portfolio optimization (e.g., Buhl & Heinrich, 2008; Tarasi et al., 2011), we assume:

1. The segments \( i = 1, 2, \ldots, I \) determine the whole customer portfolio consisting of \( N \in \mathbb{N} \) customers at the time of optimization \( t = 0 \). The portfolio share \( w_i \in [0,1] \) of each segment \( i \) is denoted by the ratio of the number of customers in the segment \( n_i \in \mathbb{N} \) and the total number of customers in the portfolio \( N \). The portfolio shares \( w_i \) are the decision variables of the customer portfolio optimization in \( t = 0 \) for the whole planning horizon \( T \). Therefore, we state:

\[
\sum_{i=1}^{I} n_i = N, \quad w_i = \frac{n_i}{N} \quad \forall i, \quad \sum_{i=1}^{I} w_i = 1
\]

The customers in each segment \( i \) generate periodic cash flows, which are influenced by several factors such as customer characteristics, price, and marketing efforts. When optimizing the ratio of fans to non-fans, a factor of particular influence needs to be considered, namely eWOM (cf. e.g., Goh et al., 2013; Rishika et al., 2013; Scholz et al., 2013). As discussed in the previous section, prior empirical research identified two main aspects of eWOM influencing cash flows, that is, its volume and sentiment (cf. Table 1). Rishika et al. (2013), for instance, confirm a higher profitability of fans compared to non-fans due to the higher volume of eWOM they are exposed to. Regarding the sentiment of
eWOM, Rishika et al. (2013) also confirm a higher profitability of fans compared to non-fans due to their higher exposure to eWOM with positive sentiment. Taken together, as fans are first exposed to a higher volume of eWOM than non-fans and second to eWOM with prevailingly positive sentiment, the expected cash flows of fans should be higher in comparison to non-fans. Consequently we assume:

\[ \begin{align*}
\text{(2)} & \quad \text{All customers in a segment } i \text{ generate (average) per capita net cash flows } CF_{i,t} \in \mathbb{R} \text{ in period } t, \text{ representing revenues minus direct variable costs (e.g., average costs for the services or products sold). In line with prior research (cf. Table 1), we state a direct relationship}^2 \text{ between the volume and sentiment of eWOM and the per capita net cash flows } CF_{i,t}^3, \text{ which are assumed to be independent and identically distributed (i.i.d.) random variables given in } t = 0 \text{ (cf. e.g., Buhl & Heinrich, 2008).}
\end{align*} \]

Costs and the time value of money need to be considered when optimizing customer portfolios in a value-based manner (Buhl & Heinrich, 2008; Ryals, 2002; 2003). One metric that fulfills these requirements is the customer lifetime value, which is widely accepted for valuing the customer base of companies in general (Gupta et al., 2004; Kumar et al., 2004) and for valuing marketing budget allocation decisions such as the promotion of fan pages in particular (Kaske et al., 2012; Ryals et al., 2007). With respect

\[ \begin{align*}
^2 & \quad \text{Our model draws on the positive (negative) effects of positive (negative) eWOM on cash flows only implicitly within this first research step. For a potential function that could be used to model this relationship explicitly, see for instance Weinberg & Berger (2011).}

^3 & \quad \text{With respect to our focus on the segments of fans and non-fans and the influence of eWOM, all further factors potentially influencing the respective cash flows (e.g., customer characteristics such as age or income level) are assumed to be deterministic and equal for both segments.}
\]
to costs, all variable costs depending on the optimal portfolio shares $w_i$ are included in the per capita net cash flows (cf. assumption 2). Fixed costs that occur independently of our customer portfolio considerations and cannot be assigned to a segment $i$ (e.g., general administration costs) do not influence the decision on the optimal portfolio shares $w_i$ and are therefore not considered in the following. As we assume that all segments $i$ are fixed over the planning horizon $T$ (cf. assumption 1), further fixed costs that can be assigned to a segment $i$ but do not depend on the number of customers $n_i$ in this segment (e.g., costs for hosting a fan page) can also be neglected (Buhl & Heinrich, 2008). To account for the time value of money, the per capita customer lifetime value $\bar{CLV}_i$ of customers in segment $i$ sums up the net present values of the per capita net cash flows $\bar{CF}_{i,t}$ over the planning horizon $T$, whereby $r_f$ represents the risk-free rate of return:

$$\bar{CLV}_i = \sum_{t=0}^{T} \frac{\bar{CF}_{i,t}}{(1+r_f)^t}$$

(2)

The expected per capita customer lifetime value $E(\bar{CLV}_i)$ of segment $i$ (shortly: $\mu_i$) is given by:

$$\mu_i = E(\bar{CLV}_i) = \sum_{t=0}^{T} \frac{E(\bar{CF}_{i,t})}{(1+r_f)^t}$$

(3)

On the basis of assumption (1) and formula (3), the expected per capita portfolio return $E(\bar{CLV}_{pp})$ (shortly: $\mu_{pp}$) can be calculated as the weighted sum of the expected customer lifetime values per capita $\mu_i$ over all segments $I$ (cf. e.g., Buhl & Heinrich, 2008):

\[\text{From a value-based management perspective, the net present values of all normalized per capita fixed costs should at least be covered by the expected per capita portfolio return given in formula (4).}\]
\[ \mu_{PF} = E(CLV_{PF}) = \sum_{i=1}^{I} w_i \mu_i \quad (4) \]

So far, our model incorporates the expected per capita net cash flows of customers in different segments. However, as discussed in the previous section, also risks associated with customer segments need to be considered when valuating customer portfolios (Dhar & Glazer, 2003; Ryals 2002; 2003). In our context, risk is induced by the fact that eWOM generated on fan pages can be positive as well as negative (cf. e.g., Goh et al., 2013; Scholz et al., 2013) and not only eWOM with positive sentiment has a positive effect on cash flows, but also eWOM with negative sentiment has a negative effect on cash flows (cf. Table 1). Taken together, the consideration of risk, that is the deviation of cash flows from their expected value, is necessary. To do so, the standard deviation has been suggested in literature on the optimization of customer portfolios (Buhl & Heinrich, 2008; Ryals et al., 2007; Sackmann et al., 2010; Tarasi et al., 2011). We consequently assume:

(3) The risk associated with the per capita net cash flows \( \bar{C}F_{i,t} \) of each segment \( i \) in period \( t \) is quantified by the standard deviation \( \sigma_{i,t} = \sqrt{Var(\bar{C}F_{i,t})} \). We assume that \( \bar{C}F_{i,t} \) are independent over \( t \) and thus can write for the standard deviation of the expected customer lifetime values \( \sigma_i \):

\[
\sigma_i = \sqrt{Var(\bar{CLV}_i)} = \sqrt{\sum_{t=0}^{T} \frac{\sigma_{i,t}^2}{(1+r)^{2t}}} = \sqrt{\sum_{t=0}^{T} \frac{Var(\bar{C}F_{i,t})}{(1+r)^{2t}}} \quad (5)
\]

(4) The portfolio risk \( \sigma_{PF} \) of the expected per capita portfolio return \( \mu_{PF} \) includes the standard deviations \( \sigma_i \) of all segments \( I \) and their covariance \( Cov_{ij} \) (cf. e.g., Buhl & Heinrich 2008):

\[
\sigma_{PF} = \sqrt{\sum_{i=1}^{I} \sum_{j=1}^{I} w_i w_j Cov(CLV_i, CLV_j)} = \sqrt{\sum_{i=1}^{I} \sum_{j=1}^{I} w_i \sigma_i w_j \sigma_j \rho_{ij}} \quad (6)
\]
whereby \( \rho_{ij} \in [0,1] \) denotes the Bravais Pearson correlation coefficient that is supposed to be strictly smaller than 1 (correlation between the per capita net cash flows of the customers in segments \( i \) are imperfect due to the assumed differences in their exposure to eWOM). The correlation coefficients \( \rho_{ij} \) are given in \( t = 0 \) and constant over the planning horizon \( T \).

Favored objective of a value-based customer portfolio management would be to maximize the expected return while minimize risk (Buhl & Heinrich, 2008; Ryals, 2007). However, as one cannot reach both objectives at the same time, a preference function is necessary. As expected return and risk have to be considered according to the individual risk preference of the decision maker, the preference function has to follow the \((\mu, \sigma)\)-rule. We assume:

(5) Every decision maker has a utility function that is compatible with the Bernoulli principle and assigns a utility for all possible values \( x \) that the random variable \( C_{\text{L}V_{PF}} \) can take. Such a utility function is given by \( u(x) = 1 - e^{-\alpha x} \). At all times, the decision maker selects the customer portfolio with the highest value of the preference function incorporating the individual level of risk aversion of the decision maker \( \alpha > 0 \), which can be represented by the Arrow-Pratt measure (Arrow, 1971; Pratt, 1964).

Based on the utility function stated in assumption (5), we can derive a preference function that integrates return and risk in accordance to the \((\mu, \sigma)\)-rule and is compatible with the Bernoulli principle (under the constraints of (approximately) normally distributed random variables \( C_{\text{L}V_i} \) and a risk averse decision maker). As the per capita net cash flows \( \bar{CF}_{it} \) are i.i.d. random variables (cf. assumption 2), it may be concluded that the expected per capita customer lifetime value \( \mu_i \) is (approximately) normally distributed (Buhl &
Heinrich, 2008; Hillier & Heebink, 1965). Therefore, we can apply the following preference function (Freund, 1956):

\[
\Phi_{\mu} (\mu_{PF}, \sigma_{PF}) = \mu_{PF} - \frac{\alpha}{2} \sigma_{PF}^2 = U_{PF} \rightarrow \max!
\]  

(7)

Based on formula (7), the optimal shares of \( w_i \) and \( w_j \), that is, an optimal allocation of customers to the different segments, can be determined by applying Markowitz portfolio theory (Markowitz, 1952; 1959).

As discussed before on the basis of existing empirical results, fans are expected to yield higher cash flows than non-fans, since they are first exposed to a higher volume of eWOM and second particularly exposed to eWOM with positive sentiment. Nevertheless, if the sentiment of eWOM generated on fan pages turns negative, the cash flows of fans are expected to decrease stronger than the cash flows of non-fans. Consequently, the cash flows generated by fans are assumed to be higher but also more risky in comparison to non-fans. Hence, no Pareto efficiency is given and the application of our model is reasonable. However, even if one of the segments (e.g., fans) actually should be Pareto efficient, our model will still provide valid results, thus ensuring practicability. Depending on the outcome regarding the optimal shares of the segments of fans and non-fans, companies face multiple levers: if the number of fans should be increased, non-fans could be approached or incentivized to become fans (e.g., by (online) marketing campaigns addressing existing or potential customers, who are not fans yet). If the number of non-fans should be increased, the customer base could be expanded by acquiring new customers, who are not fans yet (e.g., by (offline) marketing campaigns addressing potential customers, who are not likely to become fans due to their customer characteristics).
4 Demonstration and Evaluation

In this section, we demonstrate and evaluate the previously introduced model by using a case example based on real-world data from a large online retailer and publicly available data. First, we briefly introduce the online retailer and the data used for our case example. Second, we analyze the ratio between fans and non-fans by applying our model, thereby proofing its utility and validity in business practice. Third, we run a sensitivity analysis to evaluate the robustness of our model. Finally, we concisely discuss our key findings.

4.1 Introduction of the Online Retailer and Data

For demonstrating the applicability of our model in business practice, we draw on data provided by a large online retailer selling predominantly books, DVDs, computer games, and music as well as on publicly available data (cf. Table 2). The online retailer earns double-digit million Euro revenues per year and has a very successful fan page on Facebook, which is the retailer’s main online marketing channel and the major source of eWOM related to the retailer. For our demonstration and evaluation, we consider data provided by the retailer spanning 18 months and set the planning horizon accordingly. As the retailer wants to remain anonymous, all data has been slightly transformed for publication – however, all results presented in this paper qualitatively conform to the original findings derived from the genuine data set. The focus of the analysis is on the non-fans and fans, who are actual customers and thus enclosed in the underlying data set (cf. Figure 1). As already discussed in the second section, fans are connected with the respective fan page and hence directly exposed to sentiment swings on fan pages (cf. Chevalier & Mayzlin, 2006; Liu, 2006). Through their purchase, they became part of the company’s customer base and generated revenue data.
Table 2 summarizes the parameters used for demonstrating and evaluating our model.

**Table 2. Definitions, values, and sources for parameters used in case example**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>Planning horizon</td>
<td>18 month</td>
<td>Resulting from data provided by online retailer</td>
</tr>
<tr>
<td>$E(C_{\text{fans}})$</td>
<td>Expected per capita cash flows of fans in $t$</td>
<td>cf. Table 3</td>
<td>Transformed data from online retailer</td>
</tr>
<tr>
<td>$E(C_{\text{non-fans}})$</td>
<td>Expected per capita cash flows of non-fans in $t$</td>
<td>cf. Table 3</td>
<td>Transformed data from online retailer</td>
</tr>
<tr>
<td>$\sqrt{Var(C_{\text{fans}})}$</td>
<td>Std. dev. of per capita cash flows of fans in $t$</td>
<td>cf. Table 3</td>
<td>Transformed data from online retailer</td>
</tr>
<tr>
<td>$\sqrt{Var(C_{\text{non-fans}})}$</td>
<td>Std. dev. of per capita cash flows of non-fans in $t$</td>
<td>cf. Table 3</td>
<td>Transformed data from online retailer</td>
</tr>
<tr>
<td>$\rho_{\text{fans}}$</td>
<td>Bravais Pearson correlation coefficient</td>
<td>0.355</td>
<td>Calculated based on cash flows (cf. Table 3)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Arrow-Pratt measure (level of risk aversion)</td>
<td>0.15</td>
<td>Assessment of the decision maker’s individual risk aversion</td>
</tr>
<tr>
<td>$r_f$</td>
<td>Risk-free rate of return per month</td>
<td>0.12%</td>
<td>European Banking Association (Euribor)</td>
</tr>
<tr>
<td>$E(s_{\text{fans}})$</td>
<td>Expected sentiment-score in $t$</td>
<td>cf. Table 3</td>
<td>Classified data from Facebook’s Graph API</td>
</tr>
<tr>
<td>$\sqrt{Var(s_{\text{fans}})}$</td>
<td>Std. dev. of sentiment-score in $t$</td>
<td>cf. Table 3</td>
<td>Classified data from Facebook’s Graph API</td>
</tr>
</tbody>
</table>

Based on the data provided by the online retailer, we were able to derive the average per capita cash flows (calculated by average per capita revenues minus average per capita variable costs) generated by customers who are connected to the retailer’s fan page in Facebook (i.e., fans) and customers not connected to its fan page (i.e., non-fans). Besides the sheer connection to a fan page, other definitions of fans could be applied, for
example, based on their engagement with the fan page (e.g., Brodie, Ilic, Juric, & Hollebeek, 2013). However, we chose this particular operationalization, because all fans connected to a fan page are strongly exposed to eWOM generated on this particular fan page regardless of their actual engagement (as all eWOM is automatically pushed in real-time into their news feeds) (Debatin et al., 2009; Gallaugher & Ransbotham, 2010). The two segments of fans and non-fans are denoted by $i = \text{fans}, \bar{\text{fans}}$ in the following. The approximate shares of 11% fans and 89% non-fans in the retailer’s customer base could be determined by an analysis of the online retailer’s customer base (the actual values for the number of customers $N$ and the customers in the segments $n_i$ can unfortunately not be published due to confidentiality reasons).

As the online retailer’s planning period (e.g., for forecasting sales) is one month, we calculate both, the expected per capita cash flows of fans $E(\bar{CF}_{\text{fans},t})$ and non-fans $E(\bar{CF}_{\bar{\text{fans}},t})$ as well as the respective standard deviation of the per capita cash flows of fans $\sqrt{Var(\bar{CF}_{\text{fans},t})}$ and non-fans $\sqrt{Var(\bar{CF}_{\bar{\text{fans}},t})}$ on a monthly basis.

Additionally, we downloaded 7,619 user-generated wall posts and comments (eWOM) from the online retailer’s public Facebook fan page via Facebook’s Graph API. After determining the sentiment-score (numeral range from -1 “very negative” to +1 “very positive”) of each eWOM via the Free Natural Language Processing Service (loudelement.com, 2014), a free public API for sentiment analysis, we calculate the expected sentiment-score $E(\text{sentiment}_t)$ as well as the respective standard deviation of the sentiment-score $\sqrt{Var(\text{sentiment}_t)}$. Table 3 depicts both expectations and standard deviations for per capita cash flows of fans, per capita cash flows of non-fans, and sentiment-scores of eWOM on the online retailer’s Facebook fan page.
Table 3. Expected per capita cash flows and standard deviations

<table>
<thead>
<tr>
<th>Period</th>
<th>Fans (11%)</th>
<th>Non-fans (89%)</th>
<th>Sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$E(CF_{fans,t})$</td>
<td>$\sqrt{Var(CF_{fans,t})}$</td>
<td>$E(CF_{non-fans,t})$</td>
</tr>
<tr>
<td>1</td>
<td>5.78 €</td>
<td>1.99 €</td>
<td>4.99 €</td>
</tr>
<tr>
<td>2</td>
<td>5.90 €</td>
<td>2.04 €</td>
<td>5.39 €</td>
</tr>
<tr>
<td>3</td>
<td>5.59 €</td>
<td>1.54 €</td>
<td>4.79 €</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>16</td>
<td>6.05 €</td>
<td>2.16 €</td>
<td>4.97 €</td>
</tr>
<tr>
<td>17</td>
<td>4.98 €</td>
<td>1.14 €</td>
<td>4.74 €</td>
</tr>
<tr>
<td>18</td>
<td>5.91 €</td>
<td>1.75 €</td>
<td>4.93 €</td>
</tr>
</tbody>
</table>

In line with existing findings and assumptions (cf. section 2.2), a positive correlation between expected sentiment-scores and cash flows of fans can be ascertained to a 5%-level of significance (cf. Table 4). That is, the more positive the eWOM on the online retailers Facebook fan page was, the higher were the revenues by fans. In contrast, the correlation between expected sentiment-scores and non-fans is both lower and not even significant (cf. Table 4). This means that, if at all, the expected sales of non-fans are less influenced by eWOM than the expected cash flows of fans. This observation can also be confirmed by taking a look at the standard deviation of the sentiment-scores: while a higher standard deviation of the sentiment-scores is negatively correlated with the cash flows of fans to a 10%-level of significance, the correlation between the standard deviations of the sentiment-scores and the cash flows of non-fans is lower and not even significant. This means, a more polarized and heterogeneous eWOM may be, if at all, less relevant to non-fans than to fans. Summing up, eWOM significantly influences the cash flows of fans while non-fans are less affected.
Table 4. Correlation between sentiment-scores and cash flows of fans as well non-fans

<table>
<thead>
<tr>
<th></th>
<th>$E(\bar{C}_1)$</th>
<th>$E(\bar{C}_2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(\text{sentiment})$</td>
<td>0.523**</td>
<td>0.399</td>
</tr>
<tr>
<td>$\sqrt{\text{Var(\text{sentiment})}}$</td>
<td>-0.418*</td>
<td>-0.349</td>
</tr>
</tbody>
</table>

* significant at a 10%-level; ** significant at a 5%-level

Furthermore, in line with existing findings and assumptions (cf. section 2.2), the expected per capita cash flows generated by fans (cf. Table 3) apparently exceed the expected per capita cash flows generated by non-fans. This could be confirmed to a 1%-level of significance (Mean: 0.608; Std. dev.: 0.361; Std. error mean: 0.085). If the online retailer was risk neutral, it would fully concentrate on the segment of fans to increase its share to the maximum extent. However, also in line with existing findings and assumptions (cf. section 2.2), the apparently higher standard deviations of the per capita cash flows of fans (cf. Table 3) indicate a higher risk compared to non-fans. This could be confirmed to a 1%-level of significance (Mean: 1.099; Std. dev.: 1.432; Std. error mean: 0.338). Therefore, the retailer’s portfolio optimization should not be solely based on the expected per capita cash flows but also incorporate the associated risk, as proposed in our model (cf. section 2.3).

To finally apply our model, two further parameters are needed: the risk-free discount rate to calculate the expected customer lifetime values of both segments ($\mu_{\text{fans}}$ and $\mu_{\text{fanS}}$, cf. formula 3) and their standard deviations ($\sigma_{\text{fans}}$ and $\sigma_{\text{fans}}$, cf. formula 5) as well as the Arrow-Pratt measure representing the decision maker’s level of risk aversion to apply our preference function $\Phi_u(\mu_{PF}, \sigma_{PF})$. To derive the monthly risk-free discount rate $r_f$, we draw on the average annual Euribor of 1.45% in the relevant time frame of the 18 months considered in our case example (European Banking Federation, 2013). To determine the Arrow-Pratt measure representing the level of the decision maker’s risk
aversion, one could for example draw on a utility function using related market data (cf. Kasanen & Trigeorgis, 1994). Since \( \alpha/2 \) could be also interpreted as the price per unit risk (Buhl & Heinrich, 2008), it is also possible to choose that value by assessing the decision maker’s (i.e. the online retailer’s) individual risk aversion (cf. e.g., Zimmermann, Katzmarzik, & Kundisch, 2008), here leading to \( \alpha = 0.15 \). Based on these parameters, we can now analyze the ratio between fans and non-fans and its economic effects.

### 4.2 Analysis of the Ratio of Fans to Non-Fans

We first calculate the expected per capita customer lifetime values for both segments in \( t = 0 \) (\( \mu_{\text{fans}} \) and \( \mu_{\text{fan}^{-}} \), cf. formula 3), the standard deviation of the per capita customer lifetime values for both segments (\( \sigma_{\text{fans}} \) and \( \sigma_{\text{fan}^{-}} \), cf. formula 5), as well as the Bravais Pearson correlation coefficient (\( \rho_{\text{fans},\text{fan}^{-}} \)) based on the data depicted in Table 3. As the correlation coefficient \( \rho_{\text{fans},\text{fan}^{-}} = 0.355 < 1 \), the assumed imperfect correlation (cf. section 2.3) can be affirmed, thus allowing for a diversification effect in our customer portfolio. Table 5 summarizes the resulting values.

**Table 5.** Expected per capita CLV, standard deviations, and correlation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( \mu_{\text{fans}} )</th>
<th>( \mu_{\text{fan}^{-}} )</th>
<th>( \sigma_{\text{fans}} )</th>
<th>( \sigma_{\text{fan}^{-}} )</th>
<th>( \rho_{\text{fans},\text{fan}^{-}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>100.10 €</td>
<td>89.29 €</td>
<td>10.94 €</td>
<td>4.78 €</td>
<td>0.355</td>
</tr>
</tbody>
</table>

Based on the so far derived parameters, we can apply our preference function \( \Phi_u(\mu_{\text{PF}}, \sigma_{\text{PF}}) \) (cf. formula 7). Given the current allocation of fans (\( w_{\text{fans}} = 11\% \)) and non-fans (\( w_{\text{fan}^{-}} = 89\% \)), the current value of the preference function yields \( \Phi_u(\mu_{\text{PF}}, \sigma_{\text{PF}}) = 88.75 \).

Maximizing the preference function leads to an optimal share of fans (\( w_{\text{fans}}^* = 72\% \)) and non-fans (\( w_{\text{fan}^{-}}^* = 28\% \)) and a maximum value of the preference function
\( \Phi_u(\mu_{PF}, \sigma_{PF})^* = 91.72 \). For comparison, Table 6 summarizes the results for different allocation scenarios including a focus entirely on the segment of fans and non-fans, respectively.

**Table 6.** Results for different allocation scenarios

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Current allocation</th>
<th>Only fans</th>
<th>Only non-fans</th>
<th>Optimal allocation*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w_{\text{fans}} )</td>
<td>11%</td>
<td>100%</td>
<td>0%</td>
<td>72%</td>
</tr>
<tr>
<td>( w_{\text{fans}}^* )</td>
<td>89%</td>
<td>0%</td>
<td>100%</td>
<td>28%</td>
</tr>
<tr>
<td>( \mu_{PF} )</td>
<td>€90.48</td>
<td>€100.10</td>
<td>€89.29</td>
<td>€97.12</td>
</tr>
<tr>
<td>( \sigma_{PF} )</td>
<td>£4.81</td>
<td>£10.94</td>
<td>£4.78</td>
<td>£8.48</td>
</tr>
<tr>
<td>( \Phi_u(\mu_{PF}, \sigma_{PF}) )</td>
<td>88.75</td>
<td>91.12</td>
<td>87.58</td>
<td>91.72</td>
</tr>
</tbody>
</table>

**4.3 Sensitivity Analysis**

Using solely historical or forecasted data for calculating the (optimal) portfolio allocation could potentially lead to misleading results: for instance, actual future cash flows could have a higher volatility than the predicted cash flows that were used when optimizing the customer portfolio. In line with previous work (cf. e.g., Zimmermann et al., 2008), we therefore conduct a sensitivity analysis by changing one input parameter ceteris paribus (c.p.) and determining the corresponding optimal customer portfolio.

Thus, we provide insights regarding the robustness of our model and explicate how severely a 10% (c.p.) over- or underestimation of the parameters affects our initial results (cf. Table 6). In Table 7, we state the new expected per capita portfolio return (\( \mu_{PF,\text{new}}^* \)), the corresponding standard deviation (\( \sigma_{PF,\text{new}}^* \)), and the optimal portfolio shares (\( w_{\text{fans,\text{new}}}^* \) and \( w_{\text{fans,\text{new}}}^* \)) that would result when optimizing the customer portfolio based on the parameter with a ±10% change (c.p.). Moreover, we compare these results to the expected per capita portfolio return (\( \mu_{PF,\text{old}} \)) and the corresponding standard deviation (\( \sigma_{PF,\text{old}} \)) that would result when applying the parameter with a ±10% change to
the previously optimized customer portfolio with its old optimal portfolio shares \( w_{\text{fans, old}}^* = 72\% \) and \( w_{\text{non-fans, old}}^* = 28\% \) derived in the preceding section.

Table 7 highlights that the optimal allocation of customers to the segments of fans and non-fans is comparatively robust to variations (c.p.) of the standard deviation of non-fans (\( \sigma_{\text{fans}} \)), the Bravais Pearson correlation coefficient (\( \rho_{\text{fans,fans}} \)), and the level of risk aversion (\( \alpha \)). In contrast, the allocation is sensitive to variations (c.p.) of the expected per capita customer lifetime values of fans and non-fans (\( \mu_{\text{fans}}, \mu_{\text{non-fans}} \)). However, it needs to be emphasized that the high sensitivity can be traced back to the fact that both values lie close together (\( \mu_{\text{fans}} = 100.10 \) €, \( \mu_{\text{non-fans}} = 89.29 \) €). With respect to the standard deviation of the fans’ per capita customer lifetime values (\( \sigma_{\text{fans}} \)), the model is also sensitive. As rather small estimation errors can consequently lead to rather high deviations from the optimal allocation to the segments of fans and non-fans, the online retailer should especially invest in determining the value for this parameter as precisely as possible.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Initial value</th>
<th>-10%</th>
<th>+10%</th>
<th>( \mu_{\text{PF, old}} )</th>
<th>( \sigma_{\text{PF, old}} )</th>
<th>( \mu_{\text{PF, new}}^* )</th>
<th>( \sigma_{\text{PF, new}}^* )</th>
<th>( w_{\text{fans, new}}^* / w_{\text{fans, new}}^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_{\text{fans}} )</td>
<td>100.10 €</td>
<td>90.09 €</td>
<td>89.87 €</td>
<td>8.48 €</td>
<td>89.37 €</td>
<td>4.79 €</td>
<td>9% / 91%</td>
<td></td>
</tr>
<tr>
<td>( \mu_{\text{non-fans}} )</td>
<td>89.29 €</td>
<td>80.36 €</td>
<td>94.65 €</td>
<td>8.48 €</td>
<td>100.10 €</td>
<td>10.94 €</td>
<td>100% / 0%</td>
<td></td>
</tr>
<tr>
<td>( \sigma_{\text{fans}} )</td>
<td>10.94 €</td>
<td>9.85 €</td>
<td>97.12 €</td>
<td>7.70 €</td>
<td>79.07 €</td>
<td>9.08 €</td>
<td>90% / 10%</td>
<td></td>
</tr>
<tr>
<td>( \sigma_{\text{non-fans}} )</td>
<td>4.78 €</td>
<td>4.30 €</td>
<td>97.12 €</td>
<td>8.41 €</td>
<td>96.91 €</td>
<td>8.25 €</td>
<td>70% / 30%</td>
<td></td>
</tr>
<tr>
<td>( \rho_{\text{fans,fans}} )</td>
<td>0.355</td>
<td>0.3195</td>
<td>97.12 €</td>
<td>8.43 €</td>
<td>97.03 €</td>
<td>8.37 €</td>
<td>72% / 28%</td>
<td></td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.15</td>
<td>0.135</td>
<td>97.12 €</td>
<td>8.48 €</td>
<td>97.94 €</td>
<td>9.13 €</td>
<td>80% / 20%</td>
<td></td>
</tr>
</tbody>
</table>

4.4 Discussion

As discussed within the introduction, many companies host fan pages and approach or even incentivize (potential) customers to become fans in order to leverage the
considerable economic potential of eWOM generated in OSN. However, even though the sentiment of eWOM is prevalingly positive, a sheer maximization of the share of fans in a customer portfolio must be critically reflected: while fans yield higher expected cash flows than non-fans, also the associated risks in terms of these cash flows’ volatility might be considerably higher. Thus, diversifying this risk by keeping a share of non-fans – or even increasing it – might be economically reasonable. To investigate the economic effects of the ratio of fans to non-fans, we brought together preliminary findings from cross-disciplinary research in a novel, value-based manner and developed a model as our core artifact. Our contribution to theory and practice is twofold:

(1) By means of real-world data and publicly available data, we show that eWOM significantly influences the cash flows of fans while non-fans are less affected (cf. Table 4). Besides this, fans apparently hold a higher expected customer lifetime value than non-fans but also bear a higher risk in terms of the respective standard deviation (cf. Table 5). From a theoretical perspective, we therefore empirically support assumptions derived from prior research on eWOM (e.g., Rishika et al., 2013) in the context of OSN (cf. also section 2.2). Moreover, we are – to the best of our knowledge – the first quantifying the risk associated with fan pages in OSN in terms of the fans’ cash flow volatility. Thus, we extend prior research on eWOM and contribute to research focusing on economic risks in OSN. From a practical perspective, we emphasize that even though a higher expected customer lifetime value of fans is preferable, the associated risk needs to be considered. This is particularly important as our sensitivity analysis reveals a high influence of the standard deviation of the fans’ per capita customer lifetime values on the optimal customer allocation (cf. Table 7). Hence, companies should invest in mitigating this risk by preventing eWOM with negative sentiment and its viral
spread among fans to potentially reduce the standard deviation of cash flows generated by fans. This could, for instance, be facilitated by social media monitoring and sophisticated detection tools (cf. e.g., Alt & Reinhold, 2012), which allow for intervening at the very beginning when eWOM with negative sentiment is generated.

(2) The demonstration and evaluation of our artifact confirms that our proposed model for the analysis of the ratio of fans to non-fans and its economic effects “[…] works and does what it is meant to do” (“validity”, cf. Gregor & Hevner, 2013, p. 351), that is, it is feasible and leads to reasonable results. By using a case example based on real-world data provided by a large online retailer and publicly available data, we also proved the usability of our artifact in business practice (“utility”, cf. Hevner, March, Park, & Ram, 2004). By performing a sensitivity analysis, we moreover show that the model provides stable results in terms of varying parameters (“quality”, cf. Gregor & Hevner, 2013). From a theoretical perspective, we thus successfully prove the applicability of Markowitz’s Portfolio Selection Theory (Markowitz, 1952; 1959) in the context of customer portfolio management within OSN. Hence, we contribute to prior work on customer portfolio management (e.g., Buhl & Heinrich, 2008; Sackmann et al., 2010; Tarasi et al., 2011). From a practical perspective, the adaption of customer portfolio optimization on the context of fans and non-fans in customer portfolios seems reasonable and can be considered advantageous for companies. Our results suggest that it is not advisable to attract more fans without questioning the resulting economic effects and interdependencies: “Less could be more!” In the case of the online retailer used for our case example, this implies that the retailer
should aim at growing the share of fans from the current level of 11% to 72% but not to a maximum extent (e.g., by applying measures presented in section 2.3).

5 Conclusion, Limitations, and Outlook

Following the research cycle suggested by Meredith et al. (1989), we especially focused on the research stages description and explanation in order to bring together preliminary cross-disciplinary results: first, we reviewed related work regarding (1) the influence of eWOM in the purchase decision process and in OSN, (2) the effects of eWOM on the company value in general as well as on the customer value specifically, and (3) customer portfolio optimization (cf. section 2). By doing so, we aimed at providing the basis for a comprehensive overview and understanding of the problem context and linking the different research streams (description). Second, we developed a model based on these research streams (cf. section 3), which allows for an analysis of the economic effects of the ratio of fans to non-fans in a company’s customer portfolio taking into account preliminary empirical results of the economic effects of eWOM within customer lifetime value calculations (explanation). Third, we conducted an evaluation to assess the model’s validity and utility by means of a case example based on real-world data provided by a large online retailer and publicly available data (cf. section 4.1 and 4.2). Finally, we performed a sensitivity analysis (cf. section 4.3) to check the robustness of our model (testing) and discussed key findings (cf. section 4.4).

To support a rigorous definition and presentation of our artifact, we denoted it formally. Thereby, we drew on Hevner et al. (2004, p. 88), who state: “[…] to be mathematically rigorous, important parts of the problem may be abstracted […].” However, this also implies assumptions and limitations: first, we did not state and model the relationship between eWOM and per capita net cash flows explicitly. As numerous existing research already demonstrated the relationship between economic measures and
eWOM generated in OSN (cf. Table 1), we abstracted by assuming this interrelation. However, within the demonstration and evaluation of our model, we successfully tested and confirmed this assumption by means of real-world data. Furthermore, we assumed a homogeneous influence of eWOM on customers, even though prior research found that multiple factors such as homophily (e.g., Wang, Walther, Pingree, & Hawkins, 2008), trust (e.g., Xiong & Liu, 2004), tie strength (e.g., Chu & Kim, 2011), or source credibility (e.g., Wu & Wang, 2010) can lead to varying eWOM influence. Hence, a further in-depth investigation applying and extending our model within (empirical) research should be conducted in future research. Second, we focused on two segments (fans and non-fans), which does not necessarily reflect the complete reality. However, we state the model in a general form, thus making it easy to incorporate more customer segments (e.g. a finer grained segmentation based on other customer characteristics) in further, consecutive research. Third, the demonstration and evaluation of our model is based on a single case example from an online retailer selling predominantly books, DVDs, computer games, and music. Evaluating such experience goods online is particularly difficult, because their characteristics cannot be described objectively (Nelson, 1970). Therefore, eWOM as a further source of information might play a more important role in the purchase decision process when it comes to experience goods. Even though we are confident that our results can be generalized to other companies selling experience goods (e.g., books, movies, perfumes) online, further studies with empirical data of different types of companies (e.g., selling search goods) should be conducted to confirm our findings in varying settings. Fourth, potential adjustments to the existing customer portfolio, which are necessary after the portfolio optimization (e.g., acquisition of further non-fans), can be costly and raise strategic issues beyond the scope of this paper (this is in line with prior work on customer portfolio optimization, such as Tarasi et al., 2011). Therefore, “[t]he optimal [customer]
portfolio can best be viewed as an ideal customer base that managers can evaluate, revise, and assemble over time” (Tarasi et al., 2011, p. 4).

Even though these limitations leave room for future research, the paper at hand is a practically feasible step towards a value-based customer portfolio management in OSN. By suggesting a model for the analysis for the economic effects of the ratio of fans to non-fans in a company’s customer portfolio, we contribute to bridging the gap between research on economic effects of eWOM generated and disseminated within OSN and customer portfolio optimization. Thus, we provide the basis for model extensions as well as hypothesis generation and testing in the course of further iterations entirely within the meaning of the research cycle suggested by Meredith et al. (1989).
References


