ANALYZING THE IMPACT OF NEW FEATURES ON USERS' COMMUNICATION ACTIVITIES IN ONLINE SOCIAL NETWORKS

Demetz, Lukas, University of Innsbruck, Universitätsstraße 15, 6020 Innsbruck, Austria, lukas.demetz@uibk.ac.at

Heinrich, Bernd, University of Innsbruck, Universitätsstraße 15, 6020 Innsbruck, Austria, bernd.heinrich@uibk.ac.at

Klier, Mathias, University of Innsbruck, Universitätsstraße 15, 6020 Innsbruck, Austria, mathias.klier@uibk.ac.at

Abstract

Nowadays, online social networks (OSN) have become popular Internet platforms. While some of them are gathering an increasing number of users (e.g., Facebook), other OSN fail to maintain their user base (e.g., MySpace) and are confronted with a termination of their services. But what makes the difference between successful and less successful OSN? In literature, for instance, network effects, content related aspects and security mechanisms as well as the introduction of new features (e.g., Facebook's "Places" or Bebo's "Visitors Map") are generally considered to be enablers of success for OSN. However, only little research has been done so far to empirically analyze the impact of new features on users' communication activities and thus indirectly on the success of OSN. For this reason, our research examines whether the introduction of the central feature "Publisher" by Facebook caused a significant increase of users' communication activities. In order to empirically investigate this question, we use a publicly available dataset of the Facebook New Orleans Network. Moreover, among others, we adapt and use the event study methodology to be able to account for trends in the time series of users' communication activities. This leads to interesting results that do not support existing statements in literature.

Keywords: Online Social Networks, Facebook, Feature, Communication Activities, Event Study.

1.   Introduction

Since the beginning of the Web 2.0 era, a new social phenomenon has emerged on the Internet – online social networks (OSN). Following Boyd and Ellison, who use the term social network sites instead, we define OSN as *"web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system"* (Boyd and Ellison, 2007, p. 211). Nowadays, many OSN, such as Facebook and LinkedIn, have become attractive Internet platforms that enjoy great popularity. In 2008, nearly 67% of the Internet users worldwide visited OSN (Nielsen, 2009). One of the most popular OSN is Facebook, which recently exceeded the number of 500 million users (Arthur and Kiss, 2010) and is ranked within the top five most frequently visited websites in the US since 2009, measured on a weekly basis (Alexa, 2010). From September 2008 to September 2010, the number of Facebook users grew from about 33 million to more than 138 million in the US and from about 0.8 million to more than 11 million in Germany (Burcher, 2010). However, while Facebook is continuously gathering new users, other OSN struggle to keep their existing users. Some of the latter even report a decline in their user base as well as a massive decrease of visits on their websites (Radomski, 2010). Torkjazi et al. (2009), for instance, observed that the popular OSN MySpace suffers a decline in the number of its users. According to Rung (2010), nearly 50 million users abandoned MySpace between July 2007 and October 2010, reducing its user base from a total of 180 to 130 million users. This dramatic loss of users was a major reason for MySpace to rethink the strategy and to finally pass on to an entertainment platform in October 2010 (Garrahan, 2010). The OSN Bebo, which was acquired by AOL for $850 million in 2008 and – due to bad growth rates – was resold for $10 million in 2010, serves as another example for an OSN that developed less favorable (Palmer, 2010).

But what makes the difference between successful OSN and less successful OSN? It is certainly not enough to only provide a simple web-platform for users (Butler, 2001). In literature, aspects like network effects (cf. e.g. Butler, 2001; Gneiser et al., 2009; Katz and Shapiro, 1985), content related aspects (cf. e.g. Brandtzæg et al. 2010; Livingstone, 2008; Ridings and Wasko, 2010), security and privacy mechanisms (cf. e.g. Harden, 2010; Hoehne et al., 2009; Krasnova et al., 2009) as well as the development of enhanced services and *new features* (cf. e.g. Harden, 2010; Hoehne et al., 2009; Viswanath et al., 2009) are intensively discussed as enablers of success for OSN. In this paper, we refer to a feature as a functionality in terms of a set of functions or capabilities, provided by an OSN to enable identity management, relationship management and exchange of information within OSN (according to Hoehne et al., 2009). In this context, one can refer to Facebook's "Video" and "Places", Orkut's "Changing Themes" and Bebo's "Visitors Map" as examples for features.

The fact that features are regarded as critical success factors for OSN is in line with Ridings and Wasko (2010), who argue that the success of an OSN is largely determined by its users' communication activities, which in turn are said to be affected by many features. Therefore, it is not surprising that OSN providers are continuously enhancing their services by offering new features. In order to compete with YouTube, Facebook launched its video streaming service "Video" in 2007 (Cashmore, 2007), which led to approximately 100,000 videos added per day (Putnam, 2008). In August 2007, the OSN Bebo released its "Visitors Map", a feature that illustrates on a map where the last 100 visitors of a user's profile came from (Bebo, 2007). In June 2008, Orkut introduced the feature "Changing Themes", which allows users to personalize their profile pages by choosing from a set of themes (Orkut, 2008). One month later, Facebook launched a new website design that better integrated the friend feeds into the users' profiles and included a central new feature called "Publisher", providing an easier way to publish content. The feature "Publisher" allows users to send messages to other users more conveniently, including text, pictures, videos etc. (Facebook, 2008a). These messages are displayed on a message board called wall, where they can be read by other users. The wall is the most

preferred way to communicate in Facebook and is located on the profile page of each user (Wilson et al., 2009).

However, the question arises whether a central feature, such as "Publisher", really affects the users' communication activities *significantly* and thus – referring to Ridings and Wasko (2010) – contributes to the success of OSN. When looking at Facebook's new feature "Publisher", Viswanath et al. (2009) observe a sudden increase in the number of messages (here wall posts) in 2008 and link this rise in the users' communication activities to the introduction of the new feature in July 2008. Referring to a dataset of the Facebook New Orleans Network, Viswanath et al. (2009) state that *"[w]hile this sudden growth [in the number of wall posts] in mid-2008 seems abrupt, it is likely that Facebook's launch of a new site design on July 20, 2008 allowed users to more easily view wall posts through friend feeds"*. At first glance, this dependency seems to be as plain as day. Nevertheless, there exist a large number of features added to software applications that have not been successful (cf. e.g. Hsi and Potts, 2000; Lee, 2001). However, to the best of our knowledge, there is a lack of research analyzing whether the introduction of a new feature in OSN really affects the users' communication activities *significantly* and thus contributes to the vitality of an OSN. In order to address this research gap, we empirically analyze the introduction of the new feature "Publisher" by Facebook and its effect on the number of wall posts sent by the users using a publicly available dataset of the Facebook New Orleans Network. We have chosen this feature because of its importance – according to Wilson et al. (2009), the wall is Facebook's most preferred way to communicate – and its typical characteristics, which means that other OSN – like Orkut and the popular German OSN StudiVZ – introduced similar features (cf. e.g. StudiVZ, 2010). Hence, in a first step it seems reasonable to focus on the feature "Publisher" and to analyze whether the introduction of this feature has really *significantly* affected the number of users' communication activities in the Facebook New Orleans Network.

The remainder of this paper is structured as follows: In the next section, the OSN Facebook and the publicly available dataset of the Facebook New Orleans Network are introduced, which serves as the basis for our analysis. In section 3, we analyze the data and discuss our findings. Here, among others, we adapt and apply the event study methodology, which is commonly used and widely accepted in the fields of accounting and finance (cf. e.g. Boehmer et al., 1991; Brown and Warner, 1980, 1985; Fisher et al., 1969). Finally, the last section contains a conclusion and provides an outlook on future research.

2. Facebook New Orleans Network Dataset

Facebook is currently the largest OSN in the world with more than 500 million users (Arthur and Kiss, 2010). Similar to many other OSN, Facebook allows its users to create and maintain personal profiles in order to share personal information (e.g., date of birth, gender, interests, hometown) with other users. Furthermore, users can establish mutual connections and enter "friendship relations" with each other. For enabling communication within the OSN, Facebook provides several mechanisms. One of the most preferred mechanisms is called the wall (Wilson et al., 2009). It is included in every profile and serves as a message board. Users can post messages there, so-called wall posts, which may include photos, videos and links. By default, a user's wall is public, meaning that other users of Facebook are able to access the whole history of wall posts which a user received on his or her wall. However, users have the option to restrict the visibility of their wall. For instance, the history of a user's wall posts may only be accessible for those users who are connected through a friendship relation. Besides, Facebook also provides an email-like communication mechanism to exchange private messages. A special characteristic of the OSN Facebook is that users have the possibility to join subnetworks within the OSN, which typically represent universities, organizations or geographic regions, to name but a few. Most users of Facebook are members of regional networks which are open to all users. In addition, the majority of users do not change the default privacy settings (Light et al., 2008). Therefore, crawling regional networks makes it possible for researchers to gather a large fraction of a regional network's users encompassing the content of their walls as well as the friendship relations among them (Wilson et al., 2009). As a consequence, large subnetworks of Facebook can be analyzed.

For our empirical analysis we use a publicly available dataset of the Facebook New Orleans Network provided by Viswanath et al. (2009). The dataset was gathered by using a crawler that started from single users of the Facebook New Orleans Network and then visited iteratively all connected users in a breadth-first-search manner. This procedure is consistent with prior crawls of OSN (cf. e.g. Mislove et al., 2007). The crawl discovered 90,269 users, representing 52% of all users within the Facebook New Orleans Network according to the statistics provided by Facebook (Viswanath et al., 2009). However, due to changed privacy settings, the wall posts of some users could not be accessed. Consequently, the history of wall posts was gathered for a subset of 63,731 (70.6%) of all 90,269 discovered users. In total, the dataset includes 876,993 wall posts that have been initiated between September 14, 2004 and January 22, 2009, including the initiator's and receiver's identifiers as well as the corresponding timestamp. Therefore, we are able to analyze the number of wall posts that have been initiated and received by these users within the New Orleans Network over the course of time.

The dataset comprises the data of users who are part of the giant connected component[1] of the Facebook New Orleans Network (Viswanath et al., 2009). No conditions have been added when crawling the data that could have resulted in a bias within the data with regard to the research question which is focused on. Moreover, the dataset exhibits the OSN specific characteristics (e.g., concerning path length, clustering coefficient and assortativity coefficient) observed in prior research on Facebook as well as on other OSN like Orkut (Heidemann et al., 2010). Thus, the Facebook New Orleans Network dataset seems to provide a sound basis for analyzing our research question and might be representative for other regional networks of Facebook, for the Facebook Network as a whole and, to a certain extent, even for other OSN.

Figure 1 illustrates the total number of wall posts per month that have been initiated between January 1, 2007 and December 31, 2008 for all new and existing users with respect to the Facebook New Orleans Network dataset. A sudden increase in the number of wall posts can be observed in the second half of 2008. As already stated before, Facebook introduced the new feature "Publisher" on July 21, 2008. This feature provides an easier way to publish content on a user's wall (Facebook, 2008b). Thus, Facebook aimed at easing the communication between users (Facebook, 2008a).
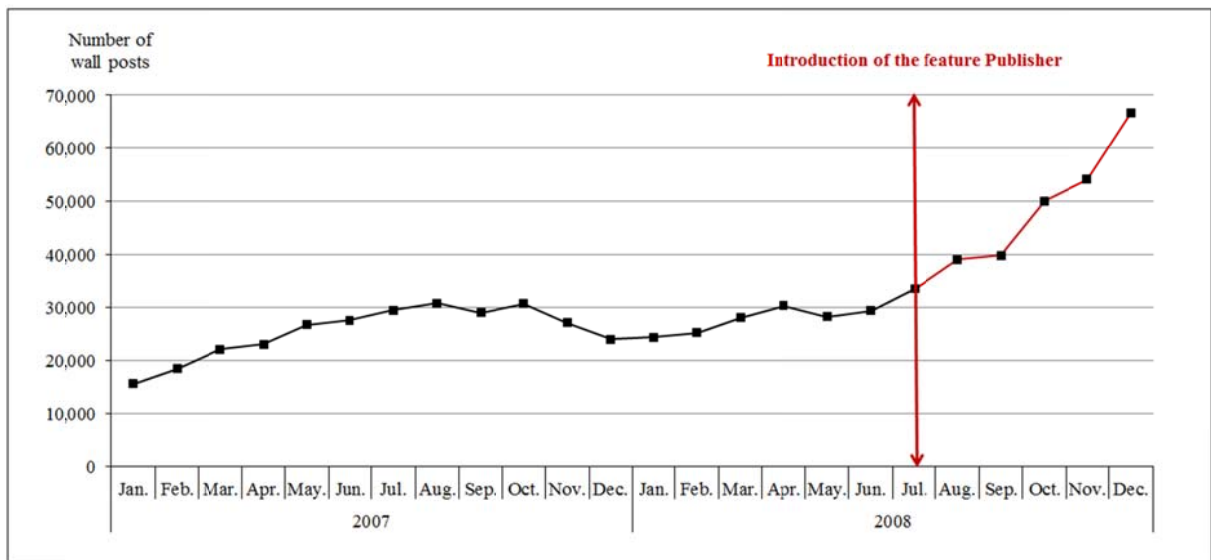

Figure 1.   *Total number of wall posts sent between January 2007 and December 2008 (with regard to the Facebook New Orleans Network dataset).*

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[1] A connected component of an OSN is characterized by the fact that, if considering the friendship relations, there exists a path between each pair of users, who are part of the component (cf. Mislove et al., 2007).

In the following, we will analyze whether the introduction of the new feature "Publisher" by Facebook has caused a significant increase in the number of wall posts of *existing* users. Here, we will deliberately focus on *existing* users, meaning users who joined the network *before* the introduction of the feature "Publisher", in order to investigate its impact on their number of sent wall posts (it is obvious that a certain extent of the increasing number of wall posts also results from new users). Hence, the aim is to find out whether the introduction of the feature has affected the communication activities of existing users *significantly* and thus may have helped to vitalize the network. Our analysis and the results will be presented in the ensuing section.

3.   Data Analysis

In order to analyze the impact of the new feature "Publisher", introduced by Facebook on July 21, 2008, we evaluate the number of wall posts in the Facebook New Orleans Network dataset that have been initiated during the six month before and after the introduction. These two timeframes are chosen to reduce the impact of short term fluctuations in the number of wall posts (e.g., because of public holidays or major sport events) and to give users a reasonable amount of time for adapting to the new feature. In order to ensure that no other major announcements or activities of Facebook within these timeframes contaminate our data, we carefully checked Facebook's press releases between January 21, 2008 and January 20, 2009. This leads to the following first hypothesis:

Hypothesis 1:

The introduction of the feature "Publisher" is positively associated with a higher average number of wall posts by the users within the Facebook New Orleans Network during the six months <u>after</u> the introduction of the feature compared to the six months <u>before</u>.

For testing this hypothesis and thus for analyzing whether the introduction of the new feature has caused a *significant* increase in the average number of wall posts by the Facebook New Orleans Network users, we act as follows: We select all users within our dataset, who joined the network before July 21, 2008[2] and wrote at least one wall post between January 21, 2008 and January 20, 2009[3]. In total, 20,948 users within the dataset fulfill these criteria. For each of the selected users the average number of wall posts per day, initiated within the six months before (from January 21, 2008 00:00 to July 20, 2008 23:59) and after (from July 21, 2008, 00:00 to January 20, 2009 23:59) the introduction of the feature "Publisher", is calculated. For users who joined the Facebook New Orleans Network after January 21, 2008, the number of days used to calculate the average number of wall posts per day before the new feature was introduced is adjusted accordingly. The following example shall illustrate this: Considering two different users, the first one joined the network before January 21, 2008 and the second one on April 21, 2008. Then, the number of wall posts during the six months before the introduction of the new feature is divided by 182 days (from January 21 to July 20, 2008 for the first user) and 91 days (from April 21 to July 20, 2008 for the second user), respectively. Taking all 20,948 users within the dataset into account, this yields the vectors $X = (X_1, \ldots, X_{20,948})$ and $Y = (Y_1, \ldots, Y_{20,948})$, containing the average number of wall posts per day before (X_i) and after (Y_i) the introduction of the new feature for each user i.

In a first step, a sign test is applied to test *Hypothesis 1* (cf. section 3.1). Due to its simplicity (Dixon and Mood, 1946) and because it can be applied to samples of all distributions (Bamberg et al., 2006), this seems to be a reasonable starting point. The sign test takes the signs of the differences between two observations into account, which means in our context a user's average number of wall posts per day before and after the introduction of the feature. However, it does not consider the differences'

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[2] It was not possible to crawl the point of time when a user joined the Facebook New Orleans Network. We therefore use the timestamp of his or her first wall post within this network, which can easily be derived from our dataset, instead.
[3] Users who did not write a wall post during this period are considered as inactive (cf. Heidemann et al., 2010).

magnitudes (Ramachandran and Tsokos, 2009). Therefore, we also apply a paired z-test (cf. section 3.2) which takes the magnitudes of these differences into account as well. However, both tests are based on aggregated data for both timeframes without considering trends etc. within the time series of wall posts. We thus refine *Hypothesis 1* and further enhance our analysis by conducting an event study in section 3.3. The event study methodology is commonly used in the fields of accounting and finance (cf. e.g. Boehmer et al., 1991; Brown and Warner, 1980, 1985; Fisher et al., 1969) to assess the impact of events, like the announcement of mergers or of changes in the upper management level, on the stock performance of a firm (Chatterjee et al., 2001). For our purpose, we adapt this methodology to analyze whether the introduction of the new feature has resulted in an "abnormal" (i.e., ex ante unexpected) increase in the number of wall posts, considering the time series of wall posts within the Facebook New Orleans Network dataset.

3.1   Sign Test

The goal of the sign test is to compare two observations under different conditions and to test the significance of the differences between these samples (Dixon and Mood, 1946). In our context, the two observations are made up of a user's average number of wall posts per day before (first condition) and after (second condition) the introduction of the feature "Publisher". Considering that the two vectors X and Y derived from our Facebook New Orleans Network dataset, the sign test is based on the signs of the differences $D_i = Y_i - X_i$ for each user i. A positive difference ($D_i > 0$) indicates that the average number of wall posts per day by user i after the introduction of the feature has been higher than before and vice versa. The test statistic T equals the number of positive differences within the N pairs of observations (X_i, Y_i):

$$T = \sum_{i=1}^{N} sign(D_i)$$

The test statistic T follows the binomial distribution with parameters (N, 0.5) (cf. Quade, 1984). In case of ties (i.e., $D_i = 0$), half of them are being counted as positive and half as negative (Dixon and Mood, 1946).

Applying the test provides the following result: For our dataset the value of the test statistic T equals 9,271 and is smaller than the critical value of 10,593 for a significance level of 0.05 (cf. Stigler, 2008). Therefore, based on our dataset, we have to conclude that the users' average number of wall posts has *not* been significantly higher in the six months after the introduction of the feature than in the six months before at the significance level of 0.05 (*Hypothesis 1* not significant). In other words, the new feature "Publisher" did not animate existing users to initiate significantly more wall posts. However, as already discussed before, the sign test does not take the magnitudes of the differences within the pairs of observations (X_i, Y_i) into account. Hence, we enhance our analysis in a second step by applying a paired z-test.

3.2   Paired Z-Test

A paired z-test is applied as a second test, which can be used to test the significance of the difference between the means of two observations under different conditions (Jones, 2002). The requirements of the paired z-test are met in our context (Bamberg et al., 2006) due to the fact that the average number of wall posts per day is measured on an interval scale and the number of pairs of observations (X_i, Y_i) is large ($N = 20,948$). Similarly to the sign test, this test is based on the differences $D_i = Y_i - X_i$ between the average numbers of wall posts per day before and after the introduction of the feature "Publisher" for each user i. The paired z-test, however, takes the differences' magnitudes D_i into consideration. The test statistic Z is defined as follows:

$$Z = \frac{\bar{z}}{\sqrt{\frac{1}{N-1} * \sum_{i=1}^{N}(D_i - \bar{z})^2}} * \sqrt{N}, \text{ where } \bar{z} = \frac{\sum_{i=1}^{N} D_i}{N}$$

Due to the central limit theorem and the large number of $N = 20,948$ pairs of observations (X_i, Y_i), the test statistic Z follows a standard normal distribution[4] (Rice, 1995). A positive value of the test statistic indicates an increase in the average number of wall posts after the introduction of the new feature and vice versa.

The test provides the following result: For our dataset the value of the test statistic Z equals -8.399 and is smaller than the critical value of 1.645 for a significance level of 0.05. In other words, even when considering the differences' magnitudes, the users' average numbers of wall posts in the six months after the feature was introduced is *not* significantly higher compared to the six months before (*Hypothesis 1* not significant). This is consistent with the results of the sign test (cf. section 3.1).

The results of both tests are quite surprising and do not support statements in literature (cf. e.g. Viswanath et al., 2009). However, both tests that have been applied so far do not consider the trends within the time series of the number of wall posts by the users. In a dynamic field like OSN (cf. e.g. Kumar et al., 2010), this seems to be rather essential. Therefore, in order to get deeper insights, we finally adapt the event study methodology, which makes it possible to take such trends into account.

3.3   Event Study

The event study methodology is commonly applied and widely accepted in accounting, finance and management studies to analyze the impact of certain events (e.g., announcements) on stock prices, for instance (Chatterjee et al., 2001). In the field of IS, the event study methodology has only been rarely used so far. Here, the papers by Dos Santos et al. (1993) and Chatterjee et al. (2001), who analyze the impact of announcements of technology investments and newly created chief information officer positions, respectively on a firm's stock market return, serve as examples. For a general discussion of the event study methodology, we refer to Brown and Warner (1980, 1985), Bowman (1986) and Boehmer et al. (1991). Traditionally, the event study methodology has been applied to analyze whether a certain event (e.g., announcement of a technology investment) is positively associated with abnormal stock market returns. In this context, the time series of stock market returns of firms that are affected by this type of event (e.g., firms announcing a technology investment), are used as a basis. The basic idea of the event study methodology is as follows: Each firm's stock market returns prior to the event (estimation window) serve as training data to estimate the stock market returns after the event (event window), not taking any possible impact of the event into consideration. These estimated stock market returns are compared to the firm's actually observed stock market returns after the event (event window). Finally, the differences between actually observed stock market returns and estimated ones in the event window are cumulated for each firm and tested for significance (N=number of firms) to analyze whether the event yields to abnormal stock market returns.

We aim to investigate whether the introduction of the feature "Publisher" by Facebook yielded a significant abnormal increase in the number of wall posts by the users in the Facebook New Orleans Network dataset. This type of research question is very similar to the ones that can be observed in the context of accounting, finance and management event studies. It deals with the analysis of the impact of a certain event (the introduction of a new feature in this case) on a dependent variable. Indeed, instead of stock market returns, we focus on the number of a user's wall posts. Nevertheless, the basic

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[4] Note that this also holds true if the observations X_i and Y_i do not follow a normal distribution (Bamberg et al., 2006). In fact, communication activities in social networks in general and the number of wall post in Facebook in particular may rather follow a power-law distribution (cf. e.g. Tyler et al., 2003; Wilson et al., 2009).

idea of the event study methodology seems to be transferable and suitable for our purpose[5]. Moreover, the Facebook New Orleans Network dataset can serve as a sound basis in this context, as no other events that could have contaminated our data occurred within the estimation and the event window. In the following, the way how to adapt and use the event study methodology is discussed accordingly. But first, we refine *Hypothesis 1* and define *Hypothesis 2* as follows:

Hypothesis 2:

The introduction of the feature "Publisher" is positively associated with an abnormal increase in the number of wall posts by the users within the Facebook New Orleans Network during the six months <u>after</u> the introduction of the feature compared to the six months <u>before</u>.

Referring to the basic idea of the event study methodology, the major steps for testing *Hypothesis 2* are summarized in Table 1.

(1)	**Analyzing the user specific trends in the number of wall posts initiated *before* the event**
	Based on the time series of each user's number of wall posts in the six months before the introduction of the feature (event), we determine a user specific estimation function that represents the user specific trend in his or her number of wall posts.
(2)	**Calculating the estimated numbers of wall posts for each user *after* the event**
	Based on the user specific estimation functions of step (1), we calculate the estimated numbers of wall posts per month by each user for the six months after the introduction of the feature. Here, it is important to note that these estimations (extrapolation) do not consider possible impacts of the event.
(3)	**Comparing *actual* and *estimated* numbers of wall posts initiated *after* the event**
	In order to determine the impact of the introduction of the new feature, we compare each user's actual and estimated (cf. step (2)) number of wall posts in the six months after the event. More specifically, for each user and month after the introduction of the feature we calculate the differences between his or her actual and estimated numbers of wall posts.
(4)	**Testing the differences between *actual* and *estimated* numbers of wall posts for significance**
	The results of step (3) – the differences between each user's actual and estimated numbers of wall posts after the introduction of the feature – serve as a basis for testing our hypothesis.

Table 1.   Steps of our event study.

In more detail, we proceed as follows: While the data basis of event studies in accounting, finance and management are mainly daily stock market returns of companies, our analysis refers to the wall posts by the users within the Facebook New Orleans Network dataset that have been initiated between January 21, 2008 00:00 (i.e., six months before the event occurred) and January 20, 2009 23:59 (i.e., six months after the event occurred). In order to be able to determine the users' trends in the number of wall posts, this timeframe is further divided into 12 single months $t = 1, …, 12$, where $t = 1$ represents the time from January 21, 2008 to February 20, 2008, $t = 2$ the time from February 21, 2008 to March 20, 2008 and so on. The aggregation of the users' wall posts by month seems to be reasonable, as the daily numbers of wall posts are too low and too volatile to determine reliable user specific trends. In contrast to the tests that have been applied in sections 3.1 and 3.2, however, only users who joined the network before January 21, 2008 and wrote at least one message before the feature was introduced are

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[5] In our context, the event study methodology has major advantages compared to the related value relevance methodology (cf. e.g. Amir et al., 1993; Amir and Lev, 1996; Barth et al., 2001) which is commonly applied in accounting as well. In the value relevance literature, *"an accounting amount is defined as value relevant if it has a predicted association with equity market values"* (Barth et al., 2001, p. 79) and stock prices, respectively. To investigate the value relevance of independent variables (e.g., accounting amounts) regarding dependent variables (e.g., stock price) regression coefficients are determined and tested for significance. However, in our context we do not focus on regression coefficients and models with given dependent and independent variables but seek to investigate whether a certain event (here, the introduction of a new feature) yielded a significant abnormal increase in the dependent variable. Therefore, the event study methodology seems to be much more apt for our purpose than the value relevance methodology.

taken into account. Setting up these conditions is necessary for having enough data to determine the user specific trends in the number of wall posts in the six months $t = 1, \ldots, 6$ before the event occurred (cf. step (1)). A total of 12,205 users of the Facebook New Orleans Network in our dataset fulfill these conditions.

For each of these users i and each month t the number of wall posts M_{it} is calculated (with $i = 1, \ldots, 12,205; t = 1, \ldots, 12$). $M_{i1}, \ldots, M_{i6}$ represent the number of wall posts that have been initiated by user i in the six months before the introduction of the feature (estimation window) and $M_{i7}, \ldots, M_{i12}$ in the six months afterwards (event window). The time series of each user's first six numbers of wall posts (i.e., $M_{i1}, \ldots, M_{i6}$) is used as training data to determine the user specific estimation functions of step (1). We conducted a pretest, based on the data of the six months before the introduction of the feature, and chose a linear regression, using the method of least squares, which is commonly applied and widely accepted in literature. In step (2), using the estimation functions of step (1), we extrapolate the user specific trends in the number of wall posts. We particularly calculate the estimated number of wall posts $\hat{M}_{it}$ that have been initiated by each user i after the introduction of the feature (i.e., $t = 7, \ldots, 12$). As the training data (i.e., $M_{i1}, \ldots, M_{i6}$) result from the six months before the event occurred, $\hat{M}_{it}$ does not consider any impacts of the introduction of the feature "Publisher". Therefore, in case of a significant impact of the new feature, the actually observed numbers of wall posts M_{it}, initiated by user i in month t ($t = 7, \ldots, 12$), should significantly differ from the estimates $\hat{M}_{it}$. In order to compare the actual and the estimated numbers of wall posts by a user i after the introduction of the feature (i.e., $t = 7, \ldots, 12$), the cumulative abnormal increase (*CAI*) in the number of wall posts is defined as follows (cf. step (3)), according to Dos Santos et al. (1993):

$$CAI_i = \sum_{t=7}^{12} M_{it} - \hat{M}_{it}$$

Thereby, a positive value for CAI_i indicates that user i has initiated more wall posts after the introduction of the feature "Publisher" than estimated and vice versa. Before testing *Hypothesis 2* on this basis (cf. step (4)), we briefly illustrate our procedure using an example.
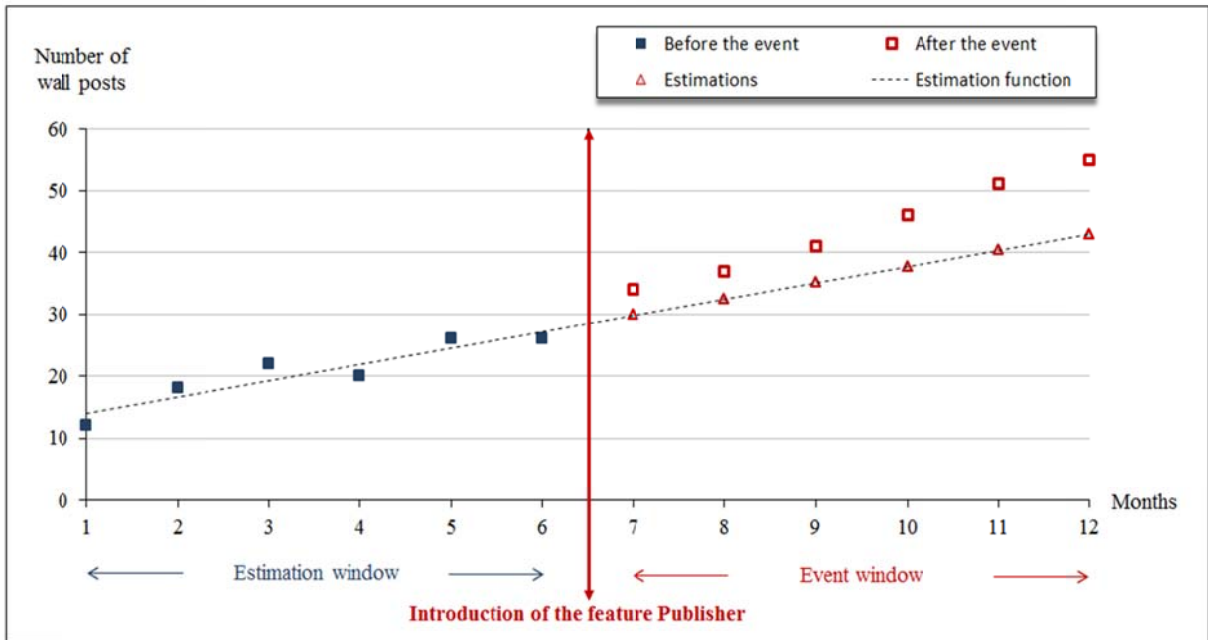

Figure 2.   *Exemplary event study for one single user.*

In Figure 2, the blue filled squares and red framed ones represent the user's actual numbers of wall posts M_{it} initiated in the six months before (estimation window) and after (event window) the introduction of the feature, respectively. The dashed line illustrates the linear estimation function based on the

user's actual number of wall posts in the estimation window. Using this estimation function provides us with the results of the user's estimated number of wall posts $\hat{M}_{it}$ (red framed triangles) in the event window (assuming that the event has no impact on the user's number of wall posts). As it can easily be observed in this figure, the user's actual numbers of wall posts after the introduction of the feature (event window) are higher than estimated. These differences lead to a positive cumulative abnormal increase CAI_i in the number of wall posts in the event window, indicating that the introduction of the feature "Publisher" might have had a positive impact on the number of wall posts by the user.

Finally, the users' cumulative abnormal increases CAI_i serve as a basis to test *Hypothesis 2* for significance (cf. step (4)). Due to the sample size of 12,205 users all prerequisites of the statistical tests conducted in sections 3.1 and 3.2 are met. As done in section 3.1, first a sign test is applied. This test gives a first indication whether an abnormal increase in the number of wall posts initiated by the users within the Facebook New Orleans Network dataset, has been caused by the introduction of the feature "Publisher". In this context, the value of the test statistic T equals the number of users i, who are characterized by a positive value for CAI_i (here, we use CAI_i instead of D_i in the formulas provided in section 3.1). For the Facebook New Orleans Network dataset, the value of the test statistic T equals 5,742 and is smaller than the critical value of 6,193 for a significance level of 0.05 and $N = 12,205$. Therefore, we have to conclude that there is no significant abnormal increase in the number of wall posts by the users after the introduction of the feature "Publisher" (*Hypothesis 2* not significant at the significance level of 0.05).

However, to additionally consider the users' cumulative abnormal increases' magnitudes CAI_i, a paired z-test is finally applied. In order to calculate the value of the test statistic Z, CAI_i is used instead of D_i in the formulas that have been provided in section 3.2. For our Facebook dataset, this results in a value of -6.082, which is again smaller than the critical value of 1.645 for a significance level of 0.05 and $N = 12,205$. Hence, in accordance with the result of the sign test, we have to conclude that *Hypothesis 2* is not significant at the significance level of 0.05.

3.4 Findings and Discussion

In July 2008, Facebook introduced a new feature called "Publisher". In literature, this feature is referred to as the reason for a sudden increase in the number of wall posts in the Facebook New Orleans Network. However, to analyze whether this feature affected the numbers of wall posts, initiated by the existing users of the network, significantly, we conducted an empirical analysis. In a first step, by applying a sign test and a paired z-test we showed that the average number of wall posts by the users within our dataset did not increase significantly after the introduction of the feature. However, both tests neglect the trends within the time series of the number of wall posts (in the considered timeframes of six months before and after the introduction of the new feature). Hence, in a second step, we explicitly addressed this issue by means of the event study methodology. In this context, a trend is understood as a fundamental tendency of the number of wall posts per user moving in a particular direction over time (e.g., continuously increasing). For instance, considering an increasing tendency of the number of wall posts per user in the months *after* the introduction of the new feature, an event study would not indicate a significant abnormal increase, if the same increasing tendency (i.e., to the same magnitude, for example) could also be observed in the months *before* the feature was introduced. In contrast, an event study would indeed indicate a significant abnormal increase, if a decreasing tendency *prior* to the introduction of the new feature was stopped because the number of wall posts afterwards remained nearly constant, for example. Thus, in contrast to analyzing highly aggregated data in terms of users' average numbers of wall posts before and after the introduction of the feature, the event study methodology takes user specific trends in the number of communication activities into account. As a consequence, the event study methodology seems to provide the deepest and most reliable results in our context. Conducting an event study in combination with a sign and a paired z-test, respectively, we indeed showed that the introduction of the new feature "Publisher" did *not* cause a significant abnormal increase in the number of wall posts by the users within our Facebook New Orleans Network dataset.

Considering these results, we argue that the introduction of the feature did not cause the sudden increase in the number of wall posts within the Facebook New Orleans Network. Even though this regional subnetwork represents a small fraction of the overall Facebook Network, the users within our dataset as well as their wall posts provide a sound basis for our purpose. On the one hand, the sample size of users within the considered dataset (e.g., 20,948 users for the tests applied in sections 3.1 and 3.2) is more than sufficient. Referring to Cochran (1977), for example, using a level of significance of 0.05, an acceptable margin of error of 0.01 and a total population of 500 million Facebook users, a minimum sample size larger or equal to 6,764 is necessary to receive reliable and valid results. On the other hand, it was shown that the Facebook New Orleans Network dataset exhibits the OSN specific characteristics (e.g., concerning path length, clustering coefficient and assortativity coefficient) that have been observed in prior research on Facebook and on other OSN (cf. Heidemann et al., 2010). Last but not least, no peculiarities of the Facebook New Orleans Network (e.g., regarding its users and their behavior) that may influence the results, were identified.

4. Conclusion and Future Research

OSN like LinkedIn or Facebook rank among the most visited websites world-wide and enjoy great popularity. However, not all OSN are successful. While some of them, like Facebook, are steadily gathering an increasing number of users, others fail to maintain their user base and are faced with a termination of their services. But what makes the difference between successful OSN and less successful OSN? According to literature, the success of an OSN is largely determined by its users' communication activities (cf. e.g. Ridings and Wasko, 2010), which in turn are said to be affected by many features that are provided by OSN. Therefore, it does not seem surprising that many OSN providers are continuously enhancing their services by offering new features. However, to the best of our knowledge, there is a lack of research that analyzes whether the introduction of a new feature in OSN affects the users' communication activities *significantly* and thus contributes to the vitality and success of an OSN. For this reason, the impact of the introduction of the feature "Publisher" by Facebook has empirically been analyzed in this paper. More precisely, the focus was on the research question whether the introduction of this feature in July 2008 caused an increase in the number of wall posts, initiated by the users within the Facebook New Orleans Network, and thus vitalized the network (i.e., increased the number of users' communication activities). For our analysis, we used a publicly available dataset of the Facebook New Orleans Network, which encompasses – for our intended purpose – a more than sufficient number of users and wall posts. In order to address the research question and thus to test our hypotheses, several statistical tests were conducted: First, we applied a sign test and a paired z-test based on each user's average number of wall posts per day, initiated before and after the introduction of the feature; second, we adapted and applied the event study methodology, which is commonly used and widely accepted in the fields of accounting and finance. This makes it possible to consider trends within the time series of the users' number of wall posts. However, according to the results of these tests, we have to conclude that Facebook's introduction of the new feature in July 2008 did not cause a significant increase in the number of wall posts that have been initiated by the users within our Facebook New Orleans Network dataset. This result is very interesting, as it does neither support the strategy of many OSN providers, namely offering continuously new features to increase the users' communication activities, nor existing statements in literature (cf. e.g. Viswanath et al., 2009).

Apart from that, the following issues may be addressed in future research. It would be interesting to analyze whether the introduction of other features (such as Facebook's location based feature "Places") had a significant impact on the vitality and thus on the success of an OSN. In addition, it is necessary to investigate which features really influence the vitality of what kind of OSN. In our initial analysis, we focused on the feature "Publisher" due to its importance within Facebook and because other OSN – such as Orkut and StudiVZ – introduced similar features. Moreover, as already mentioned before, the analyzed dataset exhibits the OSN specific characteristics (cf. Heidemann et al., 2010) and

therefore seems to be representative for other regional networks of Facebook, for Facebook as a whole and, to a certain extent, even for other OSN.

Furthermore, network externalities may be determinants of an OSN's vitality (i.e., in terms of users' communication activities) and thus of its success. Hence, it needs to be analyzed what constitutes a significant, *long term* influence on an OSN's vitality. Are new features generally important in this respect or do structural properties of an OSN, like the existence and activities of so-called "key users" (cf. Heidemann et al., 2010), play a decisive role? Especially users in an OSN, who are in a hub position (cf. Constant et al., 1996) or who occupy "structural holes" (cf. Burt, 1992), distinguish themselves in terms of a great potential for communication and interaction within networks. Hence, this group of users might be of great importance for the vitality of an entire OSN. In summary, it can be stated that the analysis that is presented in this paper, gives first insights into the investigation of the reasons for increased communication activities of users. Beyond that, we hope that it will open doors for further research activities in this exciting area.

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