Behavioral Mechanisms Prompted by Badges: The Goal-Gradient Hypothesis

Completed Research Paper

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Abstract

This paper describes our research which empirically investigates the applicability of the goal-gradient hypothesis to the activation of user contributions on a popular German Question & Answer community through badges. The goal-gradient hypothesis states that the motivation to reach a goal increases with proximity to the goal. The issue – of interest to academics and website managers alike – is to understand the role played by badges on the quantity and quality of user contributions. Our dataset enables us to measure activity levels both quantitatively and qualitatively. We find that the quantity of user contributions increases substantially in the days shortly before earning the next badge, and peak on the day of the promotion, whereas the quality of user contributions declines only slightly. Hence, our findings empirically support the goal-gradient hypothesis in the context of online communities, and provide nuanced insights into the effect of badges on online user behavior.

Keywords: Goal-Gradient Hypothesis, Online Communities, Gamification, Badges

Introduction

A key challenge for online community providers is how to turn passive users into active contributors, and how to foster and sustain the activity levels of existing contributors (e.g., Ling et al. 2005, Chen et al. 2010, Ren et al. 2012). Lately, gamification has been suggested as one of the ways by which user activity levels in online communities can be improved (e.g., Hamari & Eranti 2011, Blohm & Leimeister 2013). Gamification refers to '*using game design elements in non-gaming contexts*' (Deterding et al. 2011) in order to activate user contribution behavior and encourage social interactions between users (Hamari 2013). One popular game element to reward user achievements are so-called badges (Hamari et al. 2014). '*Badges are given to users for particular contributions to a site, such as performing a certain number of actions of a given type*' (Anderson et al. 2013). They have been implemented in a variety of fields, including educational sites (e.g., Khan Academy), social news sites (e.g., Huffington Post), knowledge-creation sites (e.g., Wikipedia), location-based social networking tools (e.g., Foursquare), and many others (e.g., Anderson et al. 2013, Denny 2013). Whilst a body of literature has recently emerged which analyzes the impact of badges on user activity levels in general (e.g., Denny 2013, Hamari, 2013), the detailed behavioral mechanisms of this phenomenon are still not fully understood. This understanding is important, however, for the optimal design of badge systems. For example, should badge systems offer only a few badges with high achievement levels or more badges with medium achievement levels? Our research enhances the understanding of these underlying behavioral mechanisms by answering the following two research questions:

1. What is the impact of proximity to the next badge on the *quantity* of user contributions?
2. What is the impact of proximity to the next badge on the *quality* of user contributions?

According to the goal-gradient hypothesis which states that the effort to reach a goal increases with proximity to the goal (e.g., Kivetz et al. 2006) we expect users to increase their activity levels in the days shortly before they are about to earn their next badge. In our research setting we evaluate user activity levels by measuring both the quantity and the quality of user contributions. Our first research question enables us to investigate whether users increase their contribution quantity with proximity to the next badge, while our second research question examines whether users behave in an opportunistic way to earn the next badge. If users substantially reduce the *quality* of their contributions (e.g., measured by the usefulness of the answers provided) while increasing their number it is not clear whether this would result in an actual increase in overall user activity levels. Alternatively, users might keep their activity levels constant and simply compensate the loss in quality with quantity. In this case, the overall benefits of a badge system might be questionable if it results in incentivizing users to produce low quality content but with an overall neutral or negative impact on overall user activity levels. This is why it is important to measure user contributions both quantitatively and qualitatively.

To address our research questions we are able to use a unique and rich dataset provided by a German Question & Answer (Q&A) community. This exclusive dataset includes detailed information about all user activity on the platform between February 2007 and May 2008. Overall, we analyze the contribution behavior of 5,828 users over a time period of 462 days. We find that users steadily increase their contribution quantitatively in the days shortly before earning a new badge, peaking on the day of the badge being awarded. At the same time, the quality of these contributions suffers only slightly from this quantitative increase. The positive effect of proximity to the new badge on contribution *quantity* is much larger compared to the negative effect it has on contribution *quality*, indicating that users really do increase their activity levels when they get closer to their goal of earning the next badge. With this paper we make novel and significant contributions to research in two ways: (1) By testing the goal-gradient hypothesis in the context of online communities and providing first empirical evidence that users continuously increase their activity levels with proximity to a badge. (2) By being the first to analyze how the quality – alongside the quantity – of user contributions is affected by badges.

Empirical Literature on Badges

Hamari et al. (2014) provide an extensive literature review about studies on gamification, which they categorize by research contexts such as commerce, learning or education, and intra-organizational systems. In Table 1, we present an excerpt from this literature review, selecting only those papers which empirically investigate the impact of badges on user activity levels.

Table 1: Overview of the Empirical Literature (Based on Hamari et al. 2014)

Research Context	Core Service	Study Design	Method	Results	Source
Commerce	Peer-to-Peer trading service	Field experiment	Statistical analysis	Partially positive	Hamari (2013)
Intra-organizational systems	Companies social network site	Field experiment	Statistical analysis	Positive	Farzan et al. (2008a)
Intra-organizational systems	Companies social network site	Field experiment	Statistical analysis	Positive	Farzan et al. (2008b)
Education/learning	Online learning tool	Field experiment	Statistical analysis	Partially positive	Denny (2013)
Education/learning	Q&A community	Observational data	Graphical inspection	-	Anderson et al. (2013)
Education/learning	Q&A community	Observational data	Graphical inspection	-	Grant & Betts (2013)

Four out of the six studies perform a randomized controlled experiment and assign users into a treatment and a control group (Hamari 2013, Denny 2013, Farzan et al. 2008a, Farzan et al. 2008b). Typically, the users in the treatment group are offered the prospect of a set of badges while the users in the control group are not. The authors compare average user contribution levels for the core activities on the corresponding platform between these two groups over a certain period of time. Hamari (2013) conducts his research in a peer-to-peer trading service and finds a positive effect of badges on the activities of a subgroup of users who actively monitor their own badges and those of others. Denny (2013) investigates the impact of a badge-based reward system on students' contributions within an online learning tool. He finds a positive effect for only one of the two analyzed activities and the number of days on which students use the tool. Farzan et al. (2008a, 2008b) evaluate the extent to which virtual points and badges encourage the contribution behavior from employees on a company's social networking site. They find that users increase their contributions quantitatively after the introduction of the virtual reward system.

Both Anderson et al. (2013) and Grant & Betts (2013) look at the effect of badges on user contribution behavior in the Q&A community Stack Overflow, a community used primarily by computer programmers interested in programming issues. The authors of both articles exploit log-files for their analysis and select a few badges to investigate their impact on the main activities of the platform, e.g., asking and answering questions. Using graphs, they plot the development of the quantity of users' contributions in the days before and after users earn a badge. Their graph analysis suggests that the quantity of the type of activity needed to earn the next badge increases in the days prior to users earning a badge.

However, two important aspects have not been addressed in the literature on badges so far:[1] (1) A rigorous empirical analysis that controls for potentially competing explanations and investigates whether the goal-gradient hypothesis also applies to badges and thus, whether user activity levels increase with proximity to a badge; (2) An analysis of how the quality of user contributions is affected by an increase in the quantity of contributions caused by badges. We add to the existing empirical literature on badges by addressing both of these aspects.

Theoretical Background

Three strands of literature are relevant to our study. The first is related to the goal setting theory, the second provides several reasons why badges can be defined as goals, while the third is concerned with the goal-gradient hypothesis.

Goal Setting Theory

The goal setting theory is a theory of motivation embedded in social psychology and states that assigning people challenging and specific goals causes them to achieve more than easy or *do your best* goals (Locke & Latham 2002). According to Bandura (1993), goals foster performance in three ways: (1) they encourage people to set higher personal goals for themselves and subsequently lead to an increase in their own efforts; (2) the self-assigned goals enhance self-efficacy and a person's belief in their ability to accomplish a task, and (3) the achievement of an allocated goal results in task satisfaction, which positively affects both self-efficacy and commitment to future goals. According to Locke and Latham (2002) the goal-performance relationship is strengthened by several moderators. Goals are effective when, for example, people are committed to them, when they receive feedback on their progress towards the goal, and when the complexity of a task is commensurate with their ability to adopt appropriate strategies to accomplish the task.

Badges as Goals

The literature has theorized several reasons why users might value badges and, thus, perceive them as valuable goals. Badges carry information about a user's past engagement, level of experience and expertise, and therefore offer useful information on which a contributor's reputation can be assessed by other users (e.g., Kollock 1990, Wasko & Faraj 2005). In this way they function as a valuable indicator for the trustworthiness of users and the reliability of the content produced by them (Antin & Churchill 2011).

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[1] In a concurrent but independent work, Goes et al. (2014) also examine the impact of proximity towards the next badge on user contribution behavior. They find that users increase their contribution levels with proximity towards the next badge and reduce their contribution levels afterwards. Our study differs in context, data granularity and scope. Goes et al. (2014) use data from an IT related community on a weekly level while we work with data from a leisure related community where users can ask everyday questions (e.g., about beauty, computers, gardening) on a daily level. We analyze user contribution behavior in the days shortly before users earn a badge and measure user activity levels both quantitatively and qualitatively. In contrast, Goes et al. (2014) measure user activity levels only quantitatively but also analyze how user activity levels change after users have earned a badge.

Moreover, and depending on context, badges represent status symbols. Here, the reward system exploits the power of status reflected in users' awareness that others will look upon them more favorably if they have accomplished the activities represented by a specific badge (e.g., Festinger 1954, Drèze & Nunes 2009). Badges may also constitute a set of activities that bind a group of users together around a common experience. Achieving badges might foster a sense of solidarity and group identification through the perception of similarity between an individual and the group (e.g., Ren et al. 2012).

Goal-Gradient Hypothesis

The goal-gradient hypothesis was originally formulated by the behaviorist C. L. Hull (1932) and states that the effort to reach a goal increases with proximity towards the goal. Most of the initial empirical work was based on experiments with animals (e.g., Hull 1934, Brown 1948, Heilizer 1977). In more recent years, several empirical studies in the field of marketing research have provided empirical evidence for the goal-gradient hypothesis based on human behavior experiments (e.g., Kivetz et al. 2006, Drèze & Nunes 2006, 2011). Kivetz et al. (2006) for example conduct a field study at a university café in which participating customers have to buy ten cups of coffee to get one coffee for free. The authors find that participants purchase coffee more frequently the closer they get to the reward.

Koo & Fishbach (2012) provide an overview of the different explanations for the goal-gradient hypothesis. Research in Gestalt psychology explains the increasing motivation to reach a goal's end state with the inherent human need for closure (Zeigarnik 1927). Work on prospect theory uses the principle of diminishing sensitivity to explain that the marginal value of each action increases with proximity towards the goal (Heath et al. 1999). Hence, *'[…] goal outcomes have a greater marginal value when they are closer to the reference point of the goal's end state, because the value function is steeper near this point'* (Koo & Fishbach 2012). A further explanation for the goal-gradient hypothesis is based on the perceived contribution of each consecutive action towards goal achievement (Brendl & Higgins 1996, Förster et al. 1998). The perceived contribution of each action increases with proximity to the goal's end state. For example, buying the first of the ten cups of coffee at the university café reduces the distance to the goal by 10% (1 out of 10 outstanding cups), whereas purchasing the last cup reduces the distance by 100% (1 out of 1 outstanding cup). Our next section describes the research environment, followed by the explicit formulation of our set of research hypotheses.

Research Environment

The website at the center of our analysis was launched in January 2006.[2] The platform offers registered and non-registered users the opportunity to ask questions to members of the community related to everyday topics (e.g., beauty, computers, gardening). In other words, the platform deals exclusively with leisure-related topics, rather than labor-market related. All registered users automatically participate in the virtual reward system of the community. There exist two types of points on the platform, status points and bonus points. After registration members start with 1,000 bonus points and 0 status points. Users earn status points for almost all the activities they perform and by accumulating status points users earn badges. In Table 2, we present a list of the main activities and the status point scheme. Approximately 99% of status points are earned by taking part in the main activities *answering* and *asking questions*.[3]

Table 2: Status Point Scheme

Main Activities	Status Points per Activity	Average of Status Points Received	Ratio of Total Status Points
Answering Questions	0 – 25	4	76%
Asking Questions	0 – 4	3	23%

[2] The operator of the website has requested to remain anonymous.

[3] There are other activities, but they play only a very minor role and account for less than 1% of the total accumulated status points (e.g., *inviting new members* to the platform).

Furthermore, users earn bonus points for answering questions. These bonus points are primarily used to incentivize other users to answer their questions in the question and answer process. The more bonus points are placed on a question (between 0 and 100), the more status points (between 0 and 25) can be earned for answering a question. Users can earn between 0 and 25 status points for an answer depending on the quality of their answer and the overall number of answers posted by other users. The quality of an answer is rated by both the questioner and by other members of the community, but only the questioner's rating is relevant for the allocation of bonus and status points. The questioner can tag an answer as *top, helpful* or *not helpful*. Answers tagged as *top* receive three times as many bonus and status points as *helpful* answers, and *not helpful* answers receive no points at all. For example, if a questioner assigns 100 bonus points to a question and tags one answer as *top* and two answers as *helpful*, then the *top* answer receives 60 bonus points and 15 status points, and each of the two *helpful* answers gets 20 bonus points and 5 status points. Apart from the activity *answering questions*, registered users can also get status points by *asking questions* to the community. The questioner receives 2 status points if a question receives at least one answer. In addition, the questioner can get 1 status point each if the question is rated as a *helpful* question by at least one other user and another point if the questioner takes the time to rate the answers to her question. No status points are earned, however, if the question remains unanswered.

As users accumulate status points, they automatically move up in an ascending ranking system of 20 hierarchical badges. For each badge users need to earn a predetermined number of status points. In Table 3 we provide a detailed list of available badges and the status points required for each badge. The labels of the first nine badges are noticeably hierarchical, such as 'Beginner', 'Student', 'Bachelor' and so on. For example, the badge 'Master' requires an accumulation of at least 1,030 status points. Based on an average of 4 status points earned per answer users would have to answer more than 250 questions to reach this badge. The list with the badges and the required status points for each badge are also publicly available on the platform. The badge and the total number of earned status points are displayed in the personal profile of each user. Both pieces of information are also publicly visible to other platform users or guests whenever a user poses or answers a question.

Table 3: List of Badges

Label of Badge	Required Status Points	Label of Badge	Required Status Points
Beginner	0	Robert Koch	8,240
Student	210	Immanuel Kant	8,740
Bachelor	530	Archimedes	9,240
Master	1,030	Max Planck	9,740
Research Assistant	1,630	Isaac Newton	10,240
Doctor	2,430	T. A. Edison	10,740
Assistant Professor	3,330	Pythagoras	11,240
Professor	4,240	Galileo Galilei	11,740
Nobel Laureates	5,240	Leonardo da Vinci	12,240
Albert Schweitzer	7,740	Albert Einstein	>12,740

Hypotheses Development

In our research environment, users might perceive badges as goals through which they can improve their status and reputation within the community. Due to the ascending order of badges, users can easily compare their relative position to other users. The badge therefore represents a user's status within the community. In addition, the badge provides information about a user's previous engagement within the community. Hence, the more valuable the badge, the higher a user's reputation is on the platform. Users who hold a superior badge might be perceived as more trustworthy and competent than newly registered users. Thus, the more valuable the badge of a user the more status points a user might receive on average as reward for an answer of the same quality. Achieving badges might also support group identification and foster solidarity with other users. Thus, by earning badges, users increase the probability of receiving high quality answers from other users when they post a question.

The goal-gradient hypothesis predicts that users increase their activity levels with proximity to the next badge. We assess user activity levels by measuring both the quantity and the quality of their contributions. Therefore, we expect users in our research setting to increase the quantity of their answers or questions in the days shortly before they earn the next badge (i.e., in proximity to the next badge). This allows us to formulate our first hypothesis:

Hypothesis I: Users continuously increase the quantity *of their contribution in the days prior to earning their next badge.*

Answers and questions can differ substantially in their quality (e.g., number of *helpful* votes). Therefore, in addition to quantity we also analyze the quality of user contributions. Following the prediction of the goal-gradient hypothesis that users increase their activity levels with proximity to the next badge, it might be that users increase the quality of their contribution as they receive more status points for higher than for lower quality contributions. However, the adjustment of the quality of their contribution could also go in the opposite direction. Motivations that are clearly incentivized by external rewards like badges can be perceived as imposing and have the effect of lowering the users' sense of self-determination (Ryan & Deci 2000, Lou et al. 2013). According to self-determination theory, motivations characterized by a low level of self-determination are only effective in activating contribution frequency but not in ensuring contribution quality (e.g., Deci et al. 1999). Thus it is conceivable that users reduce the quality of their contribution while increasing their quantity (Cabrera & Cabrera 2002). Therefore, we arrive at the following two competing hypotheses:

Hypothesis IIa: Users increase *the quality of their contribution in the days prior to earning their next badge.*

Hypothesis IIb: Users reduce *the quality of their contribution in the days prior to earning their next badge.*

Dataset, Sample & Descriptive Statistics

Dataset

We are very fortunate in having a unique dataset at our disposal – kindly provided by the operator of this Q&A community – which allows us to evaluate the impact of badges on user contribution behavior. The entire dataset covers all user activities on the platform between the beginning of February 2007 and the end of May 2008, i.e., an observation period of 462 days. During this observation period, 316,142 unregistered visitors posed a question to the community, and 73,017 new users registered on the platform. Our dataset enables us to observe what these users replied to 874,927 posted questions with 2,520,192 answers. Due to the fact that we have data on the user level, we know exactly when a user registers on the platform, when and how often this user performs a certain activity, when and how many status points she earns for her activities, and when she earns a badge.

Sample

For our empirical analysis, we aggregate the activity data on a daily level to analyze how user contribution behavior changes in the days shortly before and after a badge is earned. We restrict our sample to those users who show some commitment to the community by earning at least one badge during the observation period. Furthermore, in order to rule out potentially confounding effects (e.g., that our results are purely driven by users who take only a short time to earn the next badge) we keep only the observations in our sample where users take more than five days to earn a badge. We also drop those users from our sample (i.e., the corresponding observations) who stop to perform any of the platform's activities and thus become inactive. This leaves us with an unbalanced panel of 5,828 users and 1,302,042 observations on a daily level over a period of 462 days.

Descriptive Statistics

Activity History of Users

Table 4 presents selected descriptive statistics for our sample. On average, we observe users for 223.4 days (*Sum of Active Days*) before they become inactive and stop contributing to the platform. During the observation period, users contribute an average of 361 answers each (*Sum of Answers*) and ask 62.2 questions (*Sum of Questions*). It is worth noting at this point that the users in our sample pose altogether only 362,566 or roughly 41% of the overall questions but provide 2,103,619 or 83% of the overall answers. Thus, our sample comprises the more active contributors. Users need on average 49.6 days to earn the next badge (*Number of Days for Promotion*). As can be seen from the quantiles of the distributions, there is a strong heterogeneity in the history of user participation. The median values differ substantially from the mean values for the main activities as well as for the number of days required to reach the next badge. This reveals that a substantial share of activities is performed by a small number of top contributors.

Table 4: Users' Activity History

Variables	Mean	Min	Q25	Median	Q75	Max	Sum
Sum of Active Days	223.4	6	111	212	326	462	1,302,042
Sum of Answers	361	0	58	124	330	16,254	2,103,619
Sum of Questions	62.2	0	10	28	67	1,725	362,566
Number of Days for Promotion	49.6	6	13	25	58	460	-

Distribution of Badges

The users in our sample earn a total of 15,704 badges over the observation period. Table 5 illustrates the distribution of earned badges across the 5,828 users. When they register on the platform users automatically receive the badge 'Beginner', but from then on they need to collect more status points if they want to gain a more valuable badge. For the badge 'Student', users need to earn 210 status points (see Table 3). We observe 5,177 users who collect sufficient status points to earn this badge. In general, the more valuable a badge the fewer users earn it, as illustrated in Table 5.

Table 5: Distribution of Badges

Label of Badge	Number of Promotions	Label of Badge	Number of Promotions
Beginner	-	Robert Koch	170
Student	5,177	Immanuel Kant	149
Bachelor	3,155	Archimedes	133
Master	1,965	Max Planck	135
Research Assistant	1,427	Isaac Newton	123
Doctor	963	T. A. Edison	108
Assistant Professor	694	Pythagoras	101
Professor	517	Galileo Galilei	85
Nobel Laureates	418	Leonardo da Vinci	76
Albert Schweitzer	187	Albert Einstein	121

Our sample includes 651 users (11.2%) who were already registered on the platform before our observation period started and who hold a more valuable badge than the badge 'Beginner' at the beginning of our observation period. Thus, we do not observe all the 5,828 users in our sample earning the badge 'Student' but only 5,177 users.

Quantity Measures

For our empirical analysis, we use the number of *Answers* and the number of *Questions* per day on the user level as measures for the quantity of contributions. In Table 6, we provide mean, standard deviation, median, 95% quantile, 99% quantile, and maximum value for each of the two variables. Users provide on average 1.62 answers and ask on average 0.28 questions per day. However, on the vast majority of days, users do not actively participate on the platform.

Table 6: Quantity of Users' Contributions

Variables	Mean	Std.	Median	Q95	Q99	Max
Answers	1.62	5.60	0	10	27	218
Questions	0.28	1.17	0	2	5	140

Quality Measures

Measuring the quality of questions and answers presents a greater challenge than merely measuring the quantity of user contributions. To assess the quality of questions and answers, we define a set of proxy variables. As already mentioned, questioners can tag an answer as *top, helpful* or *not helpful* and registered users can tag an answer as *helpful*. Subsequently, an answer can receive one *top* vote but multiple *helpful* votes. Hence, we use the ratio of the number of top votes (*Top Votes/Answers*) and helpful votes per answers per day (*Helpful Votes/Answers*) on the user level respectively as the first two quality measures for answers. Moreover, previous research on article quality of Wikipedia has shown that an article's quality is correlated to its length (e.g., Blumenstock 2008). Hence, we use the ratio of the number of characters per answers per day (*Characters/Answers*) as a third measure for the quality of answers. In Table 7 we provide mean, standard deviation, median, 95% quantile, 99% quantile, and maximum value for the quality measures. On average, answers receive 0.45 helpful votes and consist of 246.5 characters (*Characters/Answers*), but only every fifth answer is rated as a top answer by the questioner (*Top Votes/Answers*). Except for the rating of the questioner, we define a similar set of quality measures for questions. We use the ratio of the number of helpful votes per questions per day (*Helpful Votes/Questions*) and the number of characters per questions per day (*Characters/Questions*) as two quality measures for questions. On average, a question receives 0.36 helpful votes from members (*Helpful Votes/Questions*) and consists of 192.8 characters (*Characters/Questions*).

Table 7: Quality of Users' Contributions

Variables	Mean	Std.	Median	Q95	Q99	Max
Top Votes/Answers	0.22	0.28	0.13	1	1	1
Helpful Votes/Answers	0.45	0.82	0.25	1.5	3	43
Characters/Answers	246.5	270.5	173	686.2	1,330	6,168
Helpful Votes/Questions	0.36	1.26	0	2	4	237
Characters/Questions	192.8	204.6	136	513.5	952	4,333

Empirical Analysis

Main Variables

To measure the impact of badges on the quantity of contributions we use the number of *Answers* and *Questions*. In addition, we take the variables *Top Votes/Answers*, *Helpful Votes/Answers* and *Characters/Answers* to measure the quality of answers, and the variables *Helpful Votes/Questions* and *Characters/Questions* to measure the quality of questions. We create a set of dummy variables, covering five days before (*Day Dummy (-5)* to *Day Dummy (-1)*), one day after users receive a badge (*Day Dummy (+1)*), and the day of the promotion itself (*Day Dummy (0)*) to elucidate how users modify the quantity and quality of their contributions in the days shortly before earning a badge, and on the day of the promotion. Additionally, to account for potential fluctuations in activity levels caused by the day of the week we create a set of dummy variables for each day of the week. Furthermore, as users can only answer questions if there are any open questions available on the platform, activity levels might vary depending on the overall number of questions that are open at any one time. An unanswered question can stay open on the platform for seven days at most. Hence we calculate the total number of questions per day as a measure of the overall activity level on the platform. By calculating the first differences of the time series we account for non-stationarity. We incorporate the first difference as well as seven lags of this variable into our model.

Contribution Quantity

Model

We start by analyzing the quantity of contributions. We estimate a poisson fixed effects model for each of the two quantity measures.[4] The model is illustrated in equation (1):

$$Y_{it} = \sum_{\tau=1}^{5} \beta_{-\tau} D_{t-\tau} + \sum_{\tau=0}^{1} \beta_{\tau} D_{t+\tau} + \sum_{\tau=1}^{6} \gamma_{\tau} WD_{\tau t} + \sum_{\tau=0}^{7} \delta_{-\tau} \Delta q_{t-\tau} + \mu_i + \varepsilon_{it} \tag{1}$$

The variable Y_{it} represents the dependent variables. Each observation in the sample is identified exactly by the index it where i represents the individual and t the day in our observation period. The variable D_t represents a dummy variable for the day on which a user earns a badge. In addition, we include 5 lags ($\beta_{-1}, \ldots, \beta_{-5}$) and 1 lead ($\beta_{+1}$) of this variable to capture average activity levels across 5 days before and one day after the promotion. In addition, we add a set of weekday dummies $WD_{\tau t}$ and the first difference as well as 7 lags of the first difference of the overall number of questions on the platform ($\delta_0, \ldots, \delta_{-7}$). Finally, we include user-specific fixed effects μ_i and the error term ε_{it} in our model.

Identification

We use individual-specific fixed effects to account for unobserved time constant heterogeneity (Wooldridge 2010). In order to examine whether badges activate user contribution behavior we compare average activity levels on the day of the promotion and on the day immediately after users were awarded a badge. Moreover, if the estimators for the variables *Day Dummy (-5)* to *Day Dummy (0)* increase in the days prior to earning the next badge, and peak on the day of the promotion, this would confirm that users increase their activity levels with proximity to the next badge.

Results

The results for the two quantity measures are illustrated in Table 8. The independent variables are presented in the first column, and the results for the number of *Answers* and *Questions* in column two and three. The estimators for the variables *Day Dummy (-5)* to *Day Dummy (+1)* reveal how the contribution quantity differs on the corresponding day. By comparing the size of these estimators we infer whether the quantity of contributions increases with proximity to the next badge. For the number of *Answers,* all estimators for the day dummies have a positive sign and are significant on a one percent level. The estimators increase continuously from 0.590 or 80% in the five days before (*Day Dummy (-5)*) to 0.863 or 137% on the day of the promotion (*Day Dummy (0)*).[5] The difference between these two

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[4] We estimate a poisson model to consider the distribution properties of both dependent variables (i.e., only non-negative integer values and large number of zeros). To account for overdispersion and autocorrelation in the data, we use cluster robust standard errors (Cameron & Trivedi 2013).

[5] We interpret the coefficients as semielasticities after exponentiating the coefficients (Cameron & Trivedi 2013). To get an approximation for the absolute effect size (e.g., number of answers per day) we multiply the relative effect (or semielasticity) with the mean value of the corresponding variable (see Table 6). For example, for the *Day Dummy (0)* we get the absolute effect of $\big((\exp(0.863) - 1\,) \times 100\,\big) \times 1.62 = 2.22$ answers per day.

estimators is 57 percentage points (ppt.) and significant on a one percent level ($\chi^2(1)=231.58$, $p<0.01$). This means that the quantity of answers increases by 57 ppt. or by approximately 0.9 answers per day.

Table 8: Analysis of Quantity of Contributions

Variables	*Answers*		*Questions*	
Day Dummy (-5)	**0.590****	(0.0252)	**0.592****	(0.0279)
Day Dummy (-4)	0.659**	(0.0254)	0.6521**	(0.0292)
Day Dummy (-3)	0.674**	(0.0293)	0.6324**	(0.0327)
Day Dummy (-2)	0.726**	(0.0269)	0.700**	(0.0296)
Day Dummy (-1)	0.793**	(0.0257)	0.882**	(0.0279)
Day Dummy (0)	**0.863****	(0.0244)	**1.413****	(0.0273)
Day Dummy (+1)	0.661**	(0.0221)	0.723**	(0.0257)
Control Variables	✓		✓	
Individual Fixed Effects	✓		✓	
Observations	1,220,523		1,177,225	
-Ln Likelihood	-2,558,810		-677,345	
Cluster Robust Standard Errors in Parentheses, ** p<0.01, * p<0.05				

However, we observe a sharp drop in the quantity of contributions on the first day after the promotion. The estimator for the *Day Dummy (+1)* is 0.661 or 94% and thus substantially lower compared to the estimator for the *Day Dummy (0)*. The difference is -43 ppt. and significant on a one percent level ($\chi^2(1)=151.42$, $p<0.01$). This reveals that users contribute approximately 0.7 fewer answers per day. We use this sharp drop in contribution quantity on the day immediately after the promotion to identify the activating effect of badges. In the chart on the left of Figure 1 we illustrate the estimators for the day dummy variables in absolute terms. The dashed vertical line represents the day of the promotion.

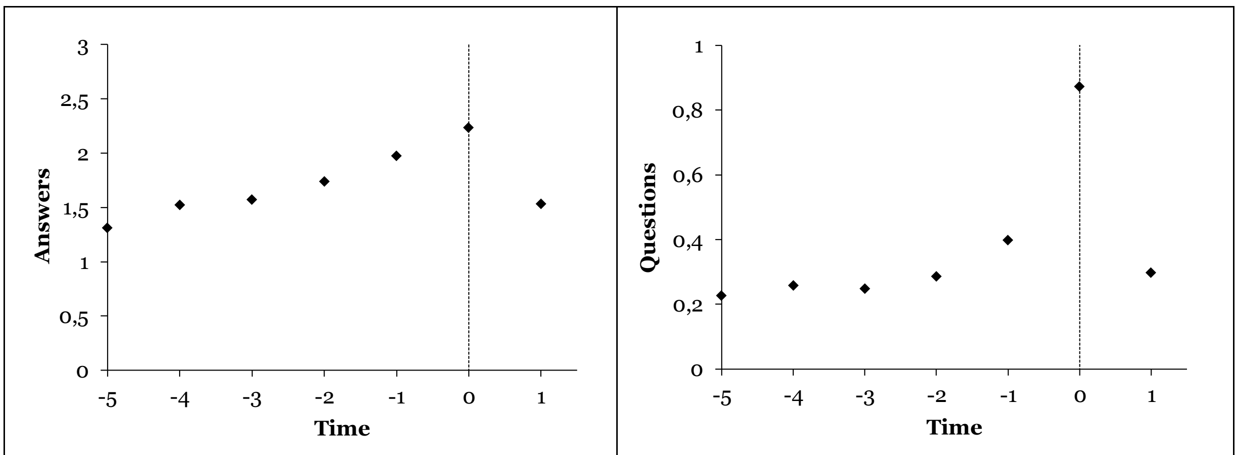

Figure 1: Quantity of Contributions

The results are equivalent for the second quantity measure, number of *Questions*. The estimators for the day dummies increase continuously from 0.592 or 81% in the five days before to 1.413 or 311% on the day of the badge being earned. The difference between these two estimators is 230 ppt. and significant on a one percent level ($\chi^2(1)=932.92$, $p<0.01$). This means that the contribution quantity increases by approximately 0.6 questions per day. On the day after the promotion the number of contributions drops sharply. The estimator for the *Day Dummy (+1)* is 0.723 or 106% and substantially lower compared to the estimator for the *Day Dummy (0)*. The difference is 205 ppt. and significant on a one percent level ($\chi^2(1)=686.87$, $p<0.01$). This means that users contribute approximately 0.6 fewer questions per day. The chart on the right of Figure 1 illustrates the estimators for the day dummy variables in absolute terms. The emerging pattern is the same as for the number of answers. The users continuously increase the number of contributions as they get closer to receiving a badge. Subsequently, we derive our first result:

RESULT I: Users substantially increase the quantity *of their contributions in the days prior to earning their next badge.*

Contribution Quality

Model

We estimate a linear fixed effects model which is illustrated in equation (2) for each quality measure. The model structure is similar to equation (1).[6]

$$Y_{it} = \alpha + \sum_{\tau=1}^{5} \beta_{-\tau} D_{t-\tau} + \sum_{\tau=0}^{1} \beta_{\tau} D_{t+\tau} + \sum_{\tau=1}^{6} \gamma_{\tau} WD_{\tau t} + \sum_{\tau=0}^{7} \delta_{-\tau} \Delta q_{t-\tau} + \mu_i + \varepsilon_{it} \tag{2}$$

Results

The results for the three measures of answer quality are presented in Table 9. The independent variables can be found in the first column, and the results for the variables *Top Votes/Answers*, *Helpful Votes/Answers* and *Characters/Answers* in column two, three and four, respectively. For the first quality measure *Top Votes/Answers*, the estimators for the *Day Dummies* are negative and significant on a one percent level. The estimator five days before the promotion is -0.0100 which means that the ratio of answers with a top vote is 4.4% lower than the base level of 0.228.[7]

Table 9: Analysis of Quality of Answers

Variables	*Top Votes/Answers*		*Helpful Votes/Answers*		*Characters/Answers*	
Day Dummy (-5)	**-0.0100****	(0.0027)	**-0.0590****	(0.0084)	**-4.759***	(2.188)
Day Dummy (-4)	-0.0090**	(0.0028)	-0.0724**	(0.0086)	-8.895**	(2.245)
Day Dummy (-3)	-0.0089**	(0.0027)	-0.0455**	(0.0092)	-7.915**	(2.351)
Day Dummy (-2)	-0.0113**	(0.0027)	-0.0639**	(0.0081)	-7.520**	(2.222)
Day Dummy (-1)	-0.0074**	(0.0026)	-0.0562**	(0.0081)	-2.714	(2.553)
Day Dummy (0)	**-0.0086****	(0.0025)	**-0.0585****	(0.0079)	**-8.288****	(2.007)
Day Dummy (+1)	-0.0082**	(0.0027)	-0.0485**	(0.0089)	-4.147	(2.336)
Constant	0.228**	(0.0015)	0.480**	(0.0045)	248.7**	(1.190)
Control Variables	✓		✓		✓	
Individual Fixed Effects	✓		✓		✓	
Observations	274,792		274,792		274,792	
Cluster Robust Standard Errors in Parentheses, ** p<0.01, * p<0.05						

The estimator on the day of the promotion is -0.0086 or -3.8%. The negative sign and the size of the estimators indicate that the ratio of top votes per answer is lower in the days before the promotion

[6] We cluster the standard errors on the user level to account for heteroscedasticity and autocorrelation in the data (Wooldridge 2010).

[7] The base level represents the *Constant* and equals the average of the user-specific fixed effects. We use the base level as reference point to interpret the size of the estimators of the *Day Dummy* variables. By dividing the estimators by the base level we get a rough approximation for the effect size in relative terms. For example, for the *Day Dummy (-5)* the approximation for the relative effect is -0.01/0.228=-4.4%.

compared to the base level. This indicates that the contribution quality is in general lower when the contribution quantity increases. However, the difference between the *Day Dummy (0)* and *Day Dummy (-5)* is 0.0014 (F(1,5724)=0.1455) and insignificant. Thus, the quality of answers does not decrease any further with proximity to the next badge. For the second quality measure *Helpful Votes/Answers*, all estimators for the *Day Dummies* are negative and significant on a one percent level. The estimator five days before the promotion is -0.0590 which means that the ratio of top answers is 12.3% lower compared to the base level of 0.480 votes per answer. The estimator on the day of the promotion is -0.0585 or -12.2%. The difference between the *Day Dummy (0)* and *Day Dummy (-5)* is 0.0005 (F(1,5724)=0.038), and therefore not significant. The chart on the left of Figure 2 illustrates the estimators for the day dummy variables. Again, the negative sign and the size of the estimators indicate that, compared to the base level, the ratio of helpful votes per answer is lower in the days before the promotion, but the estimators do not decrease with proximity to the badge.

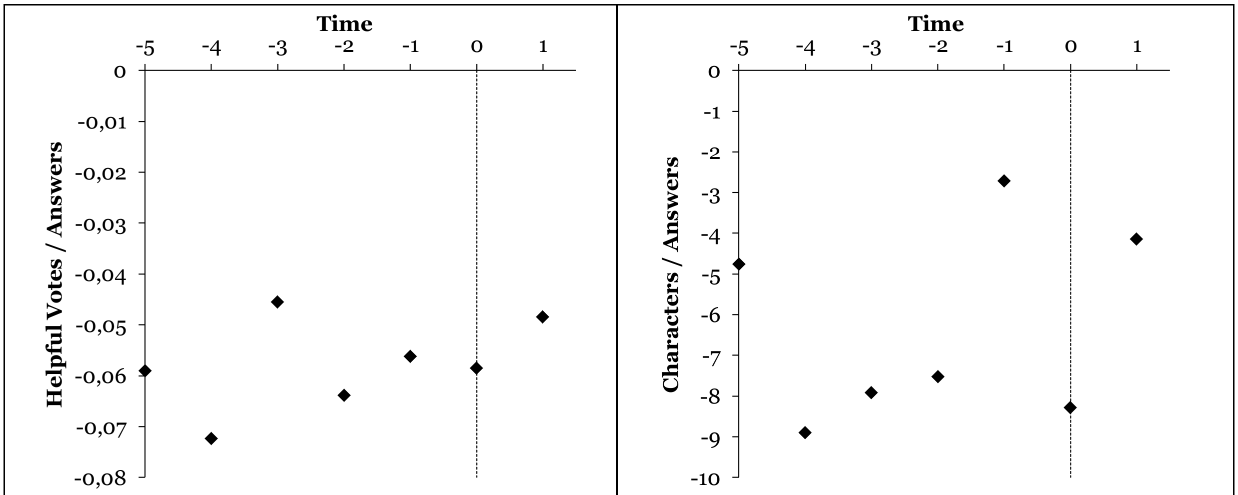

Figure 2: Quality of Answers

In the last column we present the results for the third quality measure *Characters/Answers*. The estimators for the *Day Dummies* are negative and except for the *Day Dummy (-1)* and *Day Dummy (+1)* significant. The estimator five days before the promotion is -4.759, which means that the number of characters per answer is 1.9% lower compared to the base level of 248.7 characters.[8] The estimator for the day of the promotion is -8.288 or -3.3%. The difference between the *Day Dummy (0)* and *Day Dummy (-5)* is -3.5 (F(1,5724)=1.8110, p<0.18) and not significant. The negative sign and the size of the estimators indicate that the number of characters per answer is on average slightly lower in the days preceding the promotion, compared to the base level. The estimators are illustrated in the chart on the right of Figure 2. As before, the estimators do not decrease with proximity to the next badge.

In Table 10 we illustrate the results for measures of the quality of the questions. In the first column we present the independent variables, and in columns two and three, the results for the variables *Helpful Votes/Questions* and *Characters/Questions*. For the first quality measure *Helpful Votes/Questions* the estimators for the *Day Dummies* are negative and, except for the *Day Dummy (-2) Day Dummy (0), Day Dummy (+1),* significant on a one or five percent level. The estimator for the five days preceding the promotion is -0.0636 which means that the ratio of helpful votes per question is 16.6% lower compared to the base level of 0.382 votes. The estimator for the day of the promotion is -0.0022 or -0.6%. The difference between the *Day Dummy (0)* and *Day Dummy (-5)* is 0.0614 (F(1,5422)=9.0657, p<0.01) and significant on a one percent level. The chart on the left of Figure 3 illustrates the estimators for the day dummy variables. The negative sign and the size of the estimators indicate that the ratio of helpful votes per question is lower in the days before users earn a badge.

[8] For example, the expression "Good Morning" consists of 11 characters.

Table 10: Analysis of the Quality of Question				
Variables	*Helpful Votes/Questions*		*Characters/Questions*	
Day Dummy (-5)	**-0.0636****	(0.0162)	**-8.839****	(2.946)
Day Dummy (-4)	-0.0578**	(0.0197)	-7.191*	(2.877)
Day Dummy (-3)	-0.0547**	(0.0168)	-10.84**	(2.720)
Day Dummy (-2)	-0.0167	(0.0172)	-6.574**	(2.500)
Day Dummy (-1)	-0.0559**	(0.0167)	-12.70**	(2.463)
Day Dummy (0)	**-0.0022**	(0.0161)	**-16.57****	(2.061)
Day Dummy (+1)	-0.0295	(0.0166)	-7.225*	(2.859)
Constant	0.382**	(0.0138)	197.2**	(1.267)
Control Variables	✓		✓	
Individual Fixed-Effects	✓		✓	
Observations	153,052		153,049	
Cluster Robust Standard Errors in Parentheses, ** p<0.01, * p<0.05				

Again, the negative effect does not increase with proximity to the next badge. In the last column we present the results for the second quality measure, *Characters/Questions*. The estimators for the *Day Dummies* are negative and significant. The estimator in the five days before the promotion is -8.839 which means that the number of characters per question is -4.5% lower compared to the base level of 197.2 characters. The estimator on the day of the promotion is -16.57 or -8.4%. The difference between the *Day Dummy (0)* and *Day Dummy (-5)* is -7.7288 ($F(1,5422)=5.6364$, $p<0.05$), and therefore significant. The estimators for the day dummies are illustrated in the chart on the right of Figure 3. The negative sign and the size of the estimators indicate that the number of characters per question is on average lower in the days preceding the promotion, compared to the base level. In addition, the estimators decrease slightly in the days preceding the promotion. This indicates that, while the number of questions increases, the number of characters per question decreases on average.

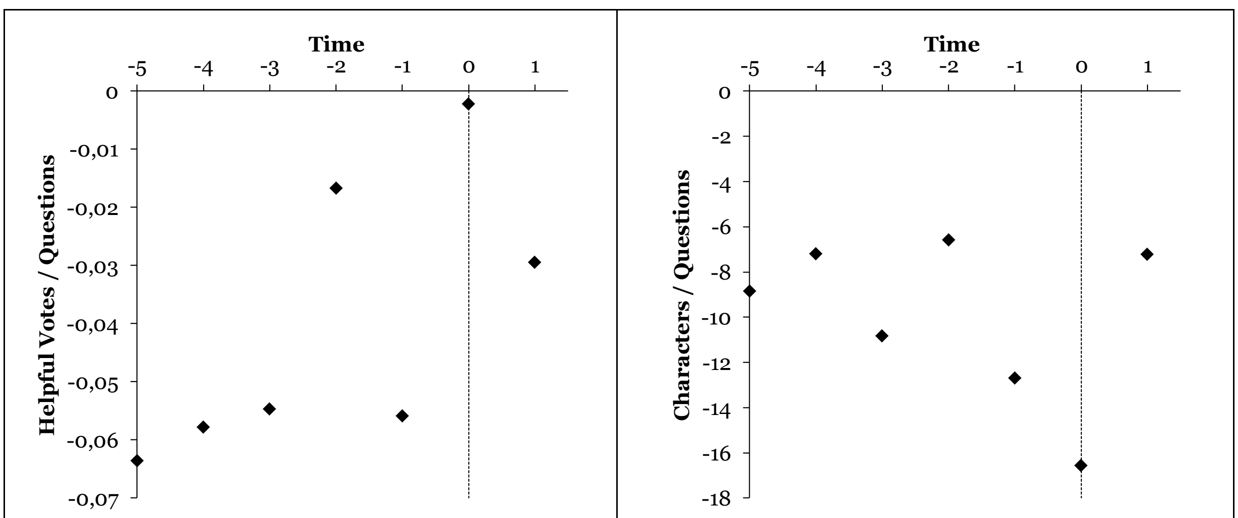

Figure 3: The Quality of Questions

By taking into account all the results of the quality measures for both answers and questions, we find that compared to the base level, the quality of contributions is lower in the days before users earn a badge. However, for most of the quality measures the negative effect hardly increases with proximity to the badge. Thus, we derive our second result:

RESULT II: The quality *of contributions diminishes only slightly when users increase the number of their contributions in the days prior to earning a badge.*

Summary of Findings

We find that users substantially increase the *quantity* of their contributions with proximity to the next badge (*RESULT I*). Thus, we find support for *HYPOTHESIS I*. At the same time, users slightly decrease the *quality* of their contributions (*RESULT II*) which supports *HYPOTHESIS IIb* and rejects the competing *HYPOTHESIS IIa*. By comparing the effect in terms of the size of the quantity and quality measures, we conclude that the overall activity levels of users increase with proximity to the next badge. Thus, we find support for the prediction of the goal-gradient hypothesis.

Robustness Checks

We examine a number of robustness checks for the quantity and quality measures, to demonstrate the robustness of our results. Robustness checks are run separately for each type of measure.

Contribution Quantity

(1) We estimate the model for each badge on the platform (see Table 3) separately; (2) We estimate the model in equation (1) as negative binomial fixed effects model; (3) we estimate our main model again by not removing from our sample the observations where users took fewer than six days to earn the next badge; (4) we adjust the set of dummy variables covering the days before users earn a badge to 3, 4, and 6 days; (5) to rule out that our results are driven by outliers we recode the values of both quantity measures which lie above the 99% quantile with the value of the quantile. For each of these robustness checks our main results remain qualitatively unchanged.

Contribution Quality

(1) We estimate the model for each badge on the platform (see Table 3) separately; (2) we log-transform our quality measures; (3) we estimate our main model again by not removing from our sample the observations where users took fewer than six days to earn the next badge; (4) we recode the values of both quantity measures which lie above the 99% quantile with the value of the quantile to rule out that our results are driven by outliers. For each of these robustness checks our main results remain qualitatively unchanged.

Conclusion

Lately, gamification has been suggested as offering a range of tools to activate user contribution levels in online communities. One very popular and widespread game element are badges. With this paper, we enhance the understanding of the underlying behavioral mechanisms prompted by badges, thus making use of the goal-gradient hypothesis which suggests that users increase their activity levels with proximity to a badge. We analyze how users modify the quantity and quality of their contributions in the days shortly before they earn a badge in a popular German Q&A community. We find that users substantially increase their contribution quantitatively for the core activities on the platform (i.e., asking and answering questions), with only slight adverse effects on the quality of their contributions. By comparing the impact of badges on the quantity and quality of contributions, we conclude that users increase their overall efforts as they approach a badge. These findings are robust and have survived a range of robustness checks.

With these results we contribute to the body of literature investigating gamification and especially how badges affect user activity levels in online communities (e.g., Hamari 2014). We also contribute to the empirical literature on the goal-gradient hypothesis (e.g., Kivetz et al. 2006, Drèze & Nunes 2006, 2011) by providing additional empirical evidence for the prevalence of the goal-gradient hypothesis in the context of online communities. Although our findings are overall consistent with the theory, we recognize that there might be other factors (e.g., the topic or thematic area of the platform) that we have not accounted for but that might also be playing a role in our research setting. While the results from the Q&A community under study may not be directly applicable to other types of online communities, our findings are, nevertheless, suggestive. Previous research in the domain of knowledge contribution in online communities has emphasized that user contribution behavior is influenced by both idealistic and altruistic factors (e.g., Krankanhalli et al. 2005, Jeppesen & Frederiksen 2006). We expect the activating effect of badges to be more pronounced in an environment where individuals are more extrinsically motivated. Thus, our results indicate that the goal-gradient hypothesis also applies to other online communities that offer some type of system to earn badges, such as Stack Overflow or Wikipedia.

The impact of virtual rewards like badges on contribution quality represents, in our opinion, a promising avenue for future research. The existing literature on contribution behavior has primarily investigated quantitative rather than qualitative aspects (e.g., Hamari et al. 2014, Lou et al. 2013). Although our study provides first empirical evidence for the slightly negative impact of badges on contribution quality, the underlying behavioral mechanisms are still not fully understood. Future research is needed to study further aspects of the impact of virtual rewards on contribution quality.

Our results also have important managerial implications. Providers of online communities and other sites (e.g., educational sites) should be aware that users increase their activity levels with proximity to a badge. Our findings indicate that virtual rewards like badges tend to activate contribution quantity rather than quality. However, in order to avoid encouraging purely opportunistic user behavior, whereby users trade contribution quality for quantity, providers might want to design systems which reward the quality as well as the quantity of contributions. If providers want to exploit the activating effect of badges they ought to take into account the predictions of the goal-gradient hypothesis when designing a badge system. The prevalence of the goal-gradient hypothesis advocates the incorporation of a set of badges with a predetermined number of required activities within a virtual reward system.

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