ExpertIdeas: Incentivizing Domain Experts to Contribute to Wikipedia

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Abstract

Authors of Wikipedia articles may not necessarily be experts on the topics they write about, leaving room for errors, misinformation, and bias. Scholars use Wikipedia as a starting point because it is quick, easy, and almost certain to have some information on a given topic. Having Wikipedia articles reviewed by reputable scholars can greatly improve the accuracy and completeness of these articles and make Wikipedia a more reliable source of knowledge. However, a large number of domain experts who use Wikipedia, as a secondary source of knowledge, have rarely if ever contributed to it. This study investigates the extent to which different incentives might motivate domain experts to contribute to Wikipedia by conducting a randomized field experiment. The results of the study demonstrate a tendency toward contributing to Wikipedia articles that are more related to the experts' recent publications, and have been more popular among domain experts. Also, making contributions identifiable significantly increases the amount of contributions. Finally, economists show a tendency toward contributing to articles that have been less popular among readers when they are not aware of this popularity.

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1 Introduction

Wikipedia is defined as a collaboratively edited, multilingual, free-access, free content online encyclopedia [40]. A great deal of the articles found in Wikipedia are comprehensive, and many entries exist in Wikipedia for which no equivalent entry may be found in any other encyclopedia. Articles are often added quickly and, as a result, coverage of current events and new technology in particular is quite extensive. Printed encyclopedias can take years to add new entries, and those entries may not cover a topic in as exhaustive detail as those in Wikipedia. While Wikipedia is a valuable and informative resource, there are some concerns with respect to its quality. Since anyone can add or change content, there is an inherent lack of reliability and stability to Wikipedia [13, 17, 20, 26, 28, 38]. Authors of articles may not necessarily be experts on the topics they write about, leaving room for error, misinformation, and bias. The founder of Wikipedia, Jimmy Wales, has stressed that Wikipedia may not be suitable for academic use, saying, ”It is pretty good, but you have to be careful with it. It’s good enough knowledge, depending on what your purpose is” [44].

Scholars use Wikipedia because it is quick, easy, and almost certain to have some information on any given topic. It is a great starting point for research with links that point to further sources. However, articles written by enthusiasts, who are not domain experts, may leave out important issues or viewpoints. Having Wikipedia articles reviewed by reputable scholars can greatly improve the accuracy and completeness of these articles and make Wikipedia a more reliable source of knowledge. Nevertheless, a large number of domain experts who use Wikipedia as a secondary source of knowledge have not contributed to it. Hoisl et al. [15] explain this phenomenon based on social loafing theory. In social psychology, social loafing is defined as ”reduction in motivation and effort when working collectively rather than individually or coactively” [18]. Hoisl et al. [15] discuss the idea that not being charged in proportion to the usage of Wikipedia makes it rational for people to use Wikipedia without contributing anything to it on their own. Considering the significant influence of domain experts’ contribution to Wikipedia, how can Wikipedia motivate domain experts to review, validate, update, or even author new articles? From another point of view, Halfaker et al. [14] explain that ”Wikipedia has changed from ’the encyclopedia that anyone can edit’ to ’the encyclopedia that anyone who understands the norms, socializes him or herself, dodges the impersonal wall of semi-automated rejection and still wants to voluntarily contribute his or her time and energy can edit’.” This change has made it more difficult and time consuming for domain experts to contribute to Wikipedia. To this end, in the literature review section, we summarize related work in the fields of social psychology and behavioral economics that try to address the problem of social loafing and free-riding, respectively, in online communities. We classify treatments introduced in these studies based on the Collective Effort Model (CEM) [18]. The majority of these studies investigate incentives to motivate members of a community to increase the volume or quality of their contribution to the community. However, very few concrete studies on the topic exist that identify motivators meant to attract non-members of a community to join and contribute to it. Moreover, the few that do exist typically prescribe a short-term approach.

In the ”theory and hypotheses” section, we discuss how this study aims to contribute to the social loafing theory, provide a practical approach for improving Wikipedia content, and explore the impact of different incentives on motivating domain experts in various fields to contribute to Wikipedia. For this purpose, we conduct a randomized field experiment. From one point of view, classic expectancy-value model and other theories of human motivation state that people will exert more effort if they believe that their effort will result in outcomes they value [5]. In addition, Self-Determination Theory (SDT) [12] explains three different forms of autonomous motivation: intrinsic, identified, and integrated motivation. Since most domain experts find less intrinsic motivation to contribute to Wikipedia, we focus on providing more identified and integrated motivation for them to contribute to Wikipedia. SDT states that it is possible that a process of internalization occurs, in which a certain behavior becomes part of the identity of a person, which in turn fosters (autonomous) motivation for this behavior, i.e., if we manage to somehow influence domain experts' values and attitudes towards contributing to Wikipedia, they will be more likely to contribute. Furthermore, SDT holds that people become motivated to engage in work based on three properties: autonomy, competence, and relatedness. Autonomy refers to a desire to experience feelings of individual freedom in how and when to perform the task; competence refers to a desire to experience feelings of control and mastery from performing a task; relatedness refers to a desire to experience feelings of connection to others from performing the task [31]. From this stand point, internalization occurs when the 3 basic psychological needs (need for competency, relatedness, and autonomy) are met. Deci et al. [9] performed a laboratory experiment to explore ways in which internalization can be promoted. They found three factors: emphasizing choice rather than control, acknowledging that people might not find the task interesting, and giving a meaningful rationale. The altruistic nature of Wikipedia intrinsically emphasizes choice rather than control. In addition, we provide the second and third factors to the subjects of our study by emphasizing the importance of their contribution in our emails to them.

In the experimental design section, we discuss the factorial design of the study and the interaction design through which we communicate with subjects of the study. We explain the way we designed email invitations in different conditions and how we framed experimental factors in them. Kittur and Kraut [19] characterize Talk pages as the most commonly used mechanism for communication in Wikipedia. They explain that "explicit coordination is especially important early in an article's lifecycle: more than half of all edits in the first week of an article are made to the discussion page rather than the content of the article." Following this argument, we leveraged this tool to provide a platform for indirect communication of domain experts and active Wikipedia editors (Wikipedians). Both domain experts and skillful Wikipedians with expertise in organizing knowledge on Wikipedia are powerful resources that we are trying to connect in order to improve the accuracy and usefulness of harnessing the wisdom of the crowd in Wikipedia.

In the method section, we characterize our hypotheses and our sampling method. Through randomized field experiments, we investigate applications of CEM's suggestions in motivating non-members of Wikipedia, as an online community, to contribute to it:

1. We make individual performance identifiable through monitoring it. We assign domain experts' names to their feedback on Wikipedia Talk pages and also acknowledge their contribution on WikiProjects.

2. We make individuals feel that their contribution to the task is necessary and relevant. We recommend Wikipedia pages related to their fields of specialty and their recent publications.

3. We make tasks more intrinsically interesting, assign meaningful tasks, and make tasks unique such that individuals feel more responsibility for their work. We inform them about the likelihood that some of their publications might be cited in Wikipedia articles.

In the analysis of the results section we explain the data that we collected in throughout the study and analyze it. In addition, we discuss our findings, evaluate our hypotheses, and based on the results, explain the mechanisms that user-generated online communities like Wikipedia can leverage to motivate non-members to join and contribute to their content.

In the appendix, we have listed different versions of the emails and web-based messages that we communicate with the subjects of the study and the interface through which they can review and comment on recommended Wikipedia articles, rate them, and refer us to other domain experts who can potentially improve the recommended articles.

This research provides insights into the mechanisms underlying incentives to motivate non-members, specifically domain experts, to join and contribute to online communities and practical guidance to design more effective incentives in similar systems.

2 Literature Review

Most studies on Wikipedia have focused on increasing the level of contribution of existing Wikipedia editors. Algan et al. [3] have provided the first field test of existing economic theories of prosocial motives for contributing to Wikipedia. They studied a diverse sample of 850 Wikipedia contributors and realized that reciprocity and social image are both strong motives for sustaining cooperation in peer production environments, while altruism is not. Zhu et al. [46] conducted a field experiment on Wikipedia to test the effects of different feedback types (positive feedback, negative feedback, directive feedback, and social feedback) on members' contributions. They also investigated the differences in how newcomers and experienced editors respond to peer feedback.

Nov [27] applied six motivational factors of volunteerism described by Clary et al. [7] to understand the activity of Wikipedia contributors:

1. **Values:** People find the opportunity to express altruistic and humanitarian concerns with others.
2. **Social:** People can find the chance to engage in activities favorable by others and be with their friends.
3. **Understanding:** By contributing to Wikipedia, people learn new things and exercise their knowledge, skills, and abilities.
4. **Career:** Wikipedia can serve as a platform to demonstrate knowledge and writing skills and an opportunity to achieve job-related benefits such as preparing for a new career or maintaining career-relevant skills or making contacts.
5. **Protective:** Wikipedia seems to provide ample opportunities for contributors to share the fortune of having knowledge with others who do not have it, reducing guilt over being more fortunate than others.
6. **Enhancement:** In Wikipedia you find the opportunity to exhibit your knowledge and have the feeling that you are needed.

Nov [27] has studied user's incentives for contribution in Wikipedia. He conducted a survey on Wikipedians and found an average level of contribution was 8.27 hours per week with ”fun” and ”ideology” being top motivators for contributing, whereas ”social”, ”career”, and ”protective” were not strong motivators. In addition, age was found to be significantly correlated with the level of some of the motivations: the older people are, the higher their motivations levels of the ”enhancement”, ”fun”, and ”protective” motivations [27]. From another point of view, Kriplean et al. [21] show that informal awards (Barnstars) are used to encourage and reward different types of valued work, and suggest that these Barnstars may be used to identify existing or emerging types of work that may correspond to different roles in Wikipedia.

In comparison with these studies on the members' contribution, there is much less research on identifying incentives to motivate non-members, such as scholars, to join online communities and contribute to them. The Wikimedia Foundation initiated an education program at U.S. universities that in 2010 encouraged government, law, and public policy students from 33 classes at 22 programs to contribute to Wikipedia[1]. Surveying 463 students in the public policy program revealed that they were motivated to work on Wikipedia articles that could reach a larger audience and could impact society more than traditional class papers. In addition, classroom characteristics and level of class engagement were strong motives to engage students to contribute in the future [22, 30]. Farzan and Kraut [11] in collaboration with the Association for Psychological Science (APS) involved 640 students from 36 courses in editing scientific articles on Wikipedia. As a result, students improved the content of over 800 articles and both students and faculty endorsed the benefits of the writing experience that would be read by a large number of people. However, asking students to contribute to Wikipedia for credit or course grade mitigates the altruistic nature of contribution to the public good. Following the behavior of these student accounts on Wikipedia after the end of the semester shows that in absence of the personal incentive, the contribution significantly decreases [11, 22]. Another unsuccessful experience of asking non-members to directly edit Wikipedia articles has been discussed by an Ecology professor at the University of Michigan who dedicated a lot of time with her students to edit Wikipedia pages. However, regardless of all of their efforts, it turned out into an edit war (constant back-and-forth reverts) with the original authors of the Wikipedia articles [10]. In a similar manner, Farzan and Kraut [11] state that ”not all the feedback from existing members was as constructive, and some established Wikipedia editors were hostile about newcomers playing in their turf.” They exemplify complaints from Ph.D. students and instructors about deletion of a large proportion of their hours of team work, by

[1] https://outreach.wikimedia.org/wiki/Education

Wikipedians. They explain that ”The nomination for deletion led to a vigorous debate, consisting of rational argument, references to policy, presentation of evidence as well as vicious name-calling. In both of these cases, students who were the targets of these attacks were understandably upset” [11]. Halfaker et al. [14] explain how this tendency to reject newcommers’ edits resulted in a decline in the number of Wikipedia editors over time. From another point of view, both Wikipedians and researchers have argued that Talk pages are critical in how content is negotiated in Wikipedia [14, 32, 37] and Talk page posts are less likely to be removed by others. To this end, we decided to provide a bridge between domain experts and Wikipedians in Wikipedia Talk pages instead of directly editing the Wikipedia articles. This bridge helps domain experts to provide their feedback to Wikipedians without making them unhappy of directly editing their work. At the same time, it lets Wikipedians decide about the importance of addressing the proposed edits and concerns in the main articles and leverages their Wikipedia editing skills to make the edits smoothly incorporated in the articles in an organized manner. We believe this strategy provides a more sustainable mechanism to motivate domain experts to contribute to Wikipedia, though the progress might be slower than asking the experts to directly edit the articles.

Most of the above mentioned studies have focused on reducing members’ social loafing on Wikipedia. Latane et al. [23] define social loafing (free-riding) as reduction in motivation and effort when working collectively rather than individually or coactively. The Karau and Williams [18]’s CEM addresses social loafing and suggests a number of ways to reduce it:

1. **Feedback:** Providing feedback about individuals’ own or their work group performance;
2. **Identifiability:** Making individual performance identifiable through monitoring it;
3. **Meaningfulness:** Assigning meaningful tasks and making tasks unique such that individuals feel more responsibility for their work;
4. **Cohesiveness:** Enhancing the cohesiveness of work groups;
5. **Necessity:** Making individuals feel that their contributions to the task are necessary and relevant;
6. **Group Value:** Improving the value of the group for the individual;
7. **Group Size:** Making groups smaller;
8. **Standards:** Providing group standards;

9. **Intrinsic Interest:** Making tasks more intrinsically interesting;

10. **Group Identity:** Making group identity or respectable others more salient.

In this study, we have developed an online system, ExpertIdeas, that provides an interactive bridge between domain experts, subjects, and the Wikipedia community, Wikipedians. Through randomized field experiments, we investigate:

1. CEM's second suggestion (identifiability) in this context:

   Many studies including Karau and Williams [18], Williams et al. [41, 42] suggest that the main factor reducing social loafing is identifiability of contribution. Through two stages of shouting experiments, Williams et al. [41] demonstrated that when individual outputs were always identifiable (even in groups), subjects consistently exerted high levels of effort, and if their outputs were never identifiable (even when alone), they consistently exerted low levels of effort across all group sizes.

   We apply the second suggestion in ExpertIdeas by grouping domain experts' names and citations to their related publications together with their feedback on Wikipedia Talk pages as a control variable and also acknowledging their contribution on WikiProjects as a treatment variable.

2. CEM's third suggestion (meaningfulness) in this context:

   We use the third suggestion via informing them about the likelihood that some of their publications might be cited in Wikipedia articles. From this perspective, this study is similar to Ling et al. [24], which attempt to tackle the problem of under-contribution in the online community called MovieLens.

3. CEM's fifth suggestion (necessity) in this context:

   We leverage the fifth suggestion as a control variable by recommending Wikipedia pages related to the subjects' fields of specialty and their recent publications.

4. CEM's seventh suggestion (group size) in this context:

   As oppose to this CEM's suggestion about the group size in terms of number of collaborators, our investigation is similar to Zhang and Zhu [45], which examines the causal relationship between group size and incentives to contribute to Chinese Wikipedia. Another early study about the effects of group size on social loafing is Valacich et al. [36]. Through a laboratory experiment they investigate the effects of group size and anonymity on group performance using a computer-mediated idea-generation system. They realized that while subjects in all conditions made the same average number of comments, larger groups generated significantly more and higher-quality ideas. They did not observe and anonymity effect on ideational performance.

Another related study is Cosley et al. [8] that provided SuggestBot for Wikipedians by leveraging the Karau and Williams [18]'s collective effort model (CEM) through reducing costs and increasing the value of outcomes in order to increase motivation. These factors can be mapped to CEM's third and fifth suggestions. ExpertIdeas considers the third factor as a control variable by reducing the edit cost on Wikipedia. For this purpose, instead of asking subjects to directly edit Wikipedia articles, we provide them with an easy-to-use user interface to read the Wikipedia articles and provide us with their feedback using a simple textbox, without dealing with Wikipedia's modeling language. Also, similar to SuggestBot, which recommends Wikipedia articles to Wikipedians based on their previous contributions, ExpertIdeas considers the fifth suggestion as a control variable by recommending Wikipedia articles to subjects based on their most recent and highly cited publications.

Moreover, ExpertIdeas provides a unique bridge between Wikipedians and domain experts. From one point of view, subjects of this study are experts in their domains of specialty. From another point of view, Wikipedians are professional Wikipedia editors, who are not only very familiar with the articles they have contributed to, but are also more strongly motivated to spend time and effort to improve their articles on Wikipedia. Connecting these two valuable sources can be considered a great advantage to Wikipedia and similar user-generated content online communities.

3 Theory and Hypotheses

This study will provide both academic and practical insights through a field experiment. We investigate incentives that Wikipedia can provide for scholars to motivate them to contribute. We ask subjects in different fields to contribute to Wikipedia by reviewing and evaluating specific Wikipedia pages. The contribution of this study to theory and application can be classified into the following categories:

1. This study contributes to social loafing theory by investigating the effects of private benefit versus public benefit on social loafing.

2. It provides a practical approach for Wikipedia to improve validity of its contents.

3. It pinpoints incentives that knowledge sharing systems can leverage to invite non-members to join and help improving their contents.

One of the closest studies is conducted by Ling et al. [24] on MovieLens. From CEM's point of view, similar to ExpertIdeas, they have focused on the second, third and fifth suggestions. They have framed CEM's second suggestion as ”believing that their contributions to the group are identifiable”, and the third and fifth suggestions as ”believing that their effort is important to the group's performance”. Furthermore, comparing MovieLens with Wikipedia, Ling et al. [24] explain that ”over 20% of the movies in MovieLens are rated by so few subscribers that the recommender system has insufficient data to provide recommendations for any user. This experiment sought to improve the quality of the MovieLens system by increasing subscribers' motivation to rate movies”. One can clearly map this statement to the problem of low contribution by domain experts to Wikipedia and the purpose of this study, which is increasing their motivation to contribute to Wikipedia.

3.1 Private Benefit

Through recommending subjects Wikipedia pages that are likely to cite their recent publications and acknowledging their contribution on Wikipedia, we investigate the effect of private benefit on their level of contribution. We expect that scholars care about their reputation. For this reason, we anticipate that likelihood of citation of their recent publications on Wikipedia articles can play as a private incentive for them to contribute to Wikipedia. We apply this hypothesis to Wikipedia by identifying related Wikipedia articles to a subject's recent research publications and recommending related Wikipedia articles.

3.2 Public Benefit

CEM's seventh suggestion discusses that making groups smaller, results in more contribution. However, CEM's suggestion has a counter effect on Zhang and Zhu [45]'s experiment. They argue that when group size is sufficiently large, pure altruistic models are not able to characterize the group size effect predicted by CEM, because in such cases ”the relative importance of pure altruism vanishes and private benefit becomes the dominant motive for contributing [4, 29]. Therefore when private benefit increases with group size, giving rise to 'social effects,' individual contribution levels could increase with group size in a large group.”

We investigate the group size effect on the level of contribution from an angle different from Zhang and

Zhu [45]. While recommending relevant Wikipedia articles to subjects' specialty area, we make them aware of the number of times people have viewed each specific recommended Wikipedia article over the month prior to the experiment. This way, they will be notified about not only the group size of the audience, but also the number of people who have read the article and are able to edit it. According to Zhang and Zhu [45]'s results, we expect showing high number of views will result in a higher level of contribution.

4 Experimental Design

ExpertIdeas invites subjects via emails containing links to study webpages. The study includes three phases: In the first phase, each scholar receives an initial email asking whether they are interested in participating in the study and editing Wikipedia articles in their area of expertise (intention-to-treat). By rejecting the initial request, they will be dropped from the study and ExpertIdeas will not send them any further emails. By positively responding to the first email, they will receive a second email with links to six study pages including Wikipedia articles to be improved. If they opt out of the study in the second phase, ExpertIdeas will not contact them anymore, otherwise if they comment on any recommended Wikipedia article, their comment will be reviewed, and if appropriate, ExpertIdeasBot[2] will post them to the Talk page [3] of the corresponding Wikipedia article and the subject will receive the third phase email. The third phase email provides them with links to their posts on the Talk pages, corresponding Wikipedia articles, and Wikipedia Getting started tutorial. The content of the emails will follow a common template, however they will vary based on the 2×3 factorial design (Table 1 on page 14). In other words, each subject will receive a randomly selected email from the 12 variations of emails: (The email templates for the first, second, and third phases are available in the appendix.)

1. With only average number of views (the Control group, shown in Appendix Figure 1);

2. With average number of views and mentioning the likelihood of their publications being cited on the recommended Wikipedia articles (Treatment 1, shown in Appendix Figure 2);

3. With average number of views, mentioning the likelihood of their publications being cited on the recommended Wikipedia articles, and acknowledging their contributions on Wikiprojects (Treatment 2, shown in Appendix Figure 3);

[2]ExpertIdeasBot is a Wikipedia Bot that we developed to post comments to Wikipedia Talk pages.

[3]https://en.wikipedia.org/wiki/Wikipedia:Talk_page_guidelines

4. With high number of views and mentioning that the recommendations will have high number of views over the past month (Treatment 3, shown in Appendix Figure 4);

5. With high number of views, mentioning that the recommendations will have high number of views over the past month, and the likelihood of their publications being cited on the recommended Wikipedia articles (Treatment 4, shown in Appendix Figure 5),

6. With high number of views, mentioning that the recommendations will have high number of views over the past month, stating the likelihood of their publications being cited on the recommended Wikipedia articles, and acknowledging their contributions on Wikiprojects (Treatment 5, shown in Appendix Figure 6),

Based on the condition that the subject belongs to, the first phase emails may follow one of the email templates demonstrated in Figures 1 to 6. Likewise, the second phase emails may fall into one of the 6 categories and corresponding email templates depicted in Figures 7 to 12. Since we do not have access to the academic titles of all subjects, in all emails, we address subjects as ”Dr.”. Moreover, in order to improve credibility of emails and increase possibility of emails being responded by the subjects, all emails and messages have been signed by two of the authors of the paper (Professor Yan Chen and Professor Robert Kraut).

It is noteworthy to mention that in order to mitigate framing effect, we framed the citation benefit into the following three phrases and ExpertIdeas randomly picks one of these phrases and incorporates it in each email including the citation benefit factor:

- Wikipedia articles that may include some of your publications in their references;
- Wikipedia articles that might refer to some of your research;
- Wikipedia articles that are likely to cite your research.

In addition, ExpertIdeas randomly alternates the order of public and private benefits in emails so that we can control for the order effect and private benefit does not always appear first.

In the first phase email (Figure 1 to 6), by clicking the first hyperlink (Yes, please send me some Wikipedia articles to comment on.) the system enters the subject into the second phase of the study and shows them the follow-up message demonstrated in Figure 25.

By clicking the second hyperlink in the first phase email (No, I am not interested.) or the last hyperlink in the second phase email (withdrawal link), the system considers the subject as not interested in receiving recommendations, stops sending emails to the subject, and shows them the follow-up message depicted in Figure 26.

By clicking the study pages' hyperlinks in the table of the second phase email, the subjects will be directed to our study pages including tools for them to review the recommended Wikipedia articles, provide us with their feedback about the article by the use of a simple textbox, rank the quality of the article, and inform us about other possible domain experts who are able to improve the specific Wikipedia article. The interface of the typical study page is depicted in Figure 27.

As the subjects have been gathered from all around the world, the time difference may play a significant role in the possibility of receiving our emails. To mitigate this confounding factor and increase the possibility of the emails being viewed by the subjects, ExpertIdeas identifies the local time in the city of the subjects' affiliations listed on their RePEc profile. The local times lets the researchers to send the emails during the day-time (6:00 AM - 7:00 PM) of the local time zone of the subject. There is also the possibility of the emails being filtered as spam and considering the high volume of emails being sent to university email servers from the ExpertIdeas' server, some servers might filter out our emails as spam or blacklist the email address. To mitigate this possibility, researchers send the emails gradually over a long period of time, having only 10 emails sent in each timestamp (every four hours). In addition, to make sure that the email address is not blacklisted, every week researchers create new email addresses in major email servers (Gmail, Outlook, Yahoo Mail) and test if the ExpertIdeas emails are being spammed. In such cases, researchers create a new email address for ExpertIdeas. In addition, in order to improve credibility of the emails and increase the possibility of emails being opened and responded by subjects, ExpertIdeas use an email address under the University of Michigan domain name and Professor Yan Chen's identity has been assigned to the email profile (si-yanchen@umich.edu).

Moreover, ExpertIdeas leverages an email tracking system to identify if the emails are being opened. In case the subject does not respond to the email after two weeks, in any phase of the study, the researchers send them a reminder email at most four times, every two weeks.

By running randomized field experiments, we hope to be able to identify incentives that induce domain experts to contribute to Wikipedia, and to contribute to public goods in general.

5 Method

We conduct a controlled field experiment by delivering different versions of an email message inviting non-members of Wikipedia to contribute to it and we expose the subjects to various types of public and private incentives as follows:

1. ***Private benefit:*** the subjects are exposed to three levels of this factor:
   (a) *No Private Benefit*;
   (b) *Citation*: indicates the likelihood of the subject's publications being cited in the Wikipedia article;
   (c) *Acknowledgement*: indicates the likelihood of the subject's publications being cited in the Wikipedia article and acknowledgment of their contribution in WikiProjects.[4]
2. ***Public benefit:*** indicates number of views of the Wikipedia article over the month prior to the experiment. The subjects are exposed to two levels of this factor:
   (a) *Average view*: only mentions the number of views of an average Wikipedia article;
   (b) *High view*: mentions the number of views of an average Wikipedia article and the selection threshold of 1,000.

In order to control for people's initial beliefs and set a benchmark for experts to compare the number of views, we mention the average number of views of Wikipedia articles in the same domain of specialty. Table 1 summarizes factorial design of this experiment:

	No Private	Citation	Acknowledgement
Average View	Control	Treatment 1	Treatment 2
High View $> 1{,}000$	Treatment 3	Treatment 4	Treatment 5

Table 1: ExpertIdeas 2×3 Factorial Design

Following this design, we investigate the following two hypotheses and answer two exploratory questions:

[4]Wikipedia defines a Wikiproject as: "A WikiProject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women's history), a specific location or a specific kind of task (for example, checking newly created pages)."

Hypothesis 1: Domain experts will be more likely to contribute more to Wikipedia when the private benefit is made salient.

Hypothesis 2: Domain experts will be more likely to contribute more to Wikipedia when the public benefit is made salient.

Two exploratory questions:

1- What type of Wikipedia articles, domain experts are more interested in contributing to? 2- Who is more interested in contributing to Wikipedia?

5.1 Sampling

Participants in this study include economists from different universities around the world, who have listed at least an English publication on their self-created RePEc profile. The subjects' full names, email addresses, and domains of expertise; and titles, full citations and keywords of their 7 most cited publications have been collected from IDEAS: Economics and Finance Research and EconPapers.[5] For each of these publications, we identified a related Wikipedia article and recommended them to the corresponding economists. The methods used to collection economists' data and Wikipedia articles are discussed in the following two parts:

5.1.1 Economists' Data Collection

RePEc.org has classified authors based on their domains of expertise at Authors at RePEc. However, authors usually belong to more than one category and these categories do not represent the experts' most recent area of focus. To convince the experts' pay attention to and open our emails, we developed a filtering algorithm to identify their most recent domain of expertise and mentioned that domain name in the subject lines of our emails. For this purpose, we used NEP reports on IDEAS and the author profiles to identify most repeated genre among their recent publications in NEP reports, and picked that category as the experts' most recent area of focus (from here on noted as "domain of expertise").

[5] According to RePEc copyright statement, we attribute RePEc as the source of the data.

The psudocode of the algorithm is as follows:

```
foreach author do
    Data: specDict := an empty dictionary of specializations (not related to NEP categories) and the
          author's # of publications under each category.
    Retrieve the author's list of publications.
    foreach publication from the most recent to the oldest one do
        Retrieve the list of NEP categories the publication belongs to.
        foreach category do
            specDict[category] += 1
            if specDict[category] == 7 then
                Result: Return the list of author's publications under this category as their recent
                        publications and the category as the author's recent field of interest.
            end
        end
    end
    Data: maxSpec := the specialization in specDict with maximum # of publications.
    Result: Return the list of author's publications under this category as their recent publications
            and the category as the author's recent field of interest.
end
```

Algorithm 1: The algorithm to identify the most recent field of focus for each expert.

As a result, our data collector gathered a total of 31,670 records of economists. Among these experts, there are 11,041 of them without any email addresses listed on their profile. So, there was no way for us to contact them. There are also 2,220 economists with email addresses but no specialization listed on their profiles. We also removed these people from the study. As a result, we obtained full information of 18,409 economists and their publications. Table 2 summarizes number of unique authors with the number of English publications in the same category (see specDict in Algorithm 1)

In the pilot study, we only targeted authors with at least 4 recent publications in the same category listed on their RePEc profile. Emails were sent to 178 unique authors in the dataset from 89 NEP categories out of 93, 2 authors in each category. 4 authors had invalid email addresses listed on their RePEc profile. We removed them from the pilot study. As a result, there were 174 subjects in our pilot study.

In the main study, we contacted the remaining 3,974 economists with at least 6 English publications

# of English Publications	**# of Unique Authors**
1	5,559
2	3,519
3	2,423
4	1,628
5	1,196
6	907
7	3,177
Total	18,409

Table 2: Number of unique Authors with minimum number of English publications in the same category.

listed on their RePEc profiles. Tables 12, 13 in appendix demonstrate domains of expertise retrieved using the algorithm 1 and the number of economists contacted in the main study under each domain.

5.1.2 Wikipedia Articles' Data Collection

For each of the 6 or 7 publications authored by the economists in the dataset, our system retrieves and recommends a Wikipedia article related to that publication. For this purpose, we use Google Custom Engine API together with a filtering algorithm to narrow down the list of possible recommended Wikipedia articles to the most relevant ones for each publication of each of the economists.

The psudocode of the algorithm is as follows:

```
foreach author do
    Data: RecommendationsDict := empty dictionary of recommendations and their # of repetition.
    foreach publication by the author do
        Data: keyword := the first keyword listed in the RePEc profile of the publication.
        recommendations = Retrieved Google search Engine API results searching (”econ+” +
          keyword);
        if |recommendations|! = 0 then
            foreach recommendation in recommendations do
                if recommendation is under the namespace 0 (Main/Article)^a ∧
                  recommendation is not edit protected^b ∧ recommendation is not a ”Stub” ∧
                  the character length of recommendation is not less than 1,500 characters^c ∧
                  recommendation has not been viewed less than 1,000 times over the past 30 days^d
                 then
                    Result: Save recommendation as one of the recommendations for publication.
                    Increment # of repetition of recommendation in RecommendationsDict.
                end
            end
        end
    end
    foreach publication by the author do
        Result: Save the most repeated recommendation as the recommendation for publication.
    end
end
```

Algorithm 2: The algorithm to identify the most recent field of focus for each expert.

[a] Other types of Wikipedia articles that are not appropriate for the purpose of recommending to economists include: ”Talk”, ”User”, ”User talk”, ”Wikipedia”, ”Wikipedia talk”, ”File”, ”File talk”, ”MediaWiki”, ”MediaWiki talk”, ”Template”, ”Template talk”, ”Help”, ”Help talk”, ”Category”, ”Category talk”, ”Portal”, ”Portal talk”, ”Wikipedia”, ”Wikipedia talk”, ”Book”, ”Book talk”, ”Draft”, ”Draft talk”, ”Education Program”, ”Education Program talk”, ”TimedText”, ”TimedText talk”, ”Module”, ”Module talk”, ”Gadget”, ”Gadget talk”, ”Gadget definition”, ”Gadget definition talk”, ”Special”, ”Special talk”, ”Media”, ”Media talk”. A complete list of Wikipedia articles namespaces and their definitions are available at: Wikipedia:Namespace - Wikipedia.

[b] Edit protected Wikipedia articles are not appropriate for the purpose of recommending to economists. A comprehensive explanation of Wikipedia protection policy is available at: Wikipedia:Protection policy - Wikipedia.

[c] ”Stub” Wikipedia articles are not appropriate for the purpose of recommending to economists. However, a number of economists asked us to provide them with the commenting interface on specific Wikipedia articles classified as Stub. So, there are few Stubs included in our dataset. A comprehensive explanation of Stub Wikipedia articles is available at: Wikipedia:Stub - Wikipedia.

[d] This restriction is due to the ”high-view” (public benefit) condition in the design of the experiment. In order to prevent sample selection bias, all restrictions with less than 1,000 views over the past 30 days have been excluded from the study.

6 Analysis of the Results

This chapter, first overviews different characteristics of the participants in this study and multiple features of the Wikipedia articles recommended to these domain experts. Evidence is provided to support randomization of the participants and the recommended Wikipedia articles among the control and treatments groups. It follows with the analysis of the results in each phase of the study and discussion about the methods used in the analysis.

6.1 Participants' Characteristics and Features of the Recommendations

6.1.1 Participants' Characteristics

Participants of this study consist of 3,974 economists with at least 6 English publications on their RePEc profiles. Through their self-created profiles on `RePEc.org`, we have collected the following characteristics of these participants. Table 3 presents the summary statistics of these characteristics.

Variable	# of Observations	Mean	Standard Deviation	Minimum	Maximum
Related Field	3,974	.00377	.0613	0	1
Author Abstract Views	3,921	26,306	2,165.272	11	46,057
Top 10%	3,974	.367	.482	0	1
US Affiliation	3,974	.215	.411	0	1
English Affiliation	3,974	.441	.497	0	1
# of Recommendations	3,974	5.779	.630	1	6

Table 3: Participants' characteristics summary statistics

- **Domains of expertise (Related Field)**: as defined in algorithm 1, we characterize domain of expertise as the most recent field of research of each economist identified by the algorithm. Tables 12, 13 in appendix demonstrate domains of expertise and the number of economists contacted in the main study under each domain. Among these domains, the following three are related to the domain of expertise of one of the authors of this paper whose signature is at the end of all the emails to the economists:
  - Behavioral and Experimental Economics,
  - Experimental Economics,
  - Cognitive and Behavioral Economics.

Through field experiment on Wikipedia, Algan et al. [3] show that reciprocity and social image are both strong motives for sustaining cooperation in peer production environments, while altruism is not. So, we hypothesize those economists whose recent field of research is identified as one of the above three domains might respond differently to our email invitations in comparison with those in other domains. Hence, in our analysis we define the dummy variable ”Related Field” that indicates if the economist’s recent field of research is one of the above three domains.

- **Author Abstract Views**[6]: we conducted the experiment over May to November 2016. Although the recommendations were retrieved a week before the beginning of the experiment, the economists’ data were retrieved from RePEc.org one year prior to the experiment. The field ”Author Abstract Views” in our dataset shows the number of times each economists’ publication abstracts on `RePEc.org` have been viewed over the year 2016. The rationale for choosing this period of time is to ensure all economists in this study have had an active profile on RePEc with at least 6 publications with English abstract and keywords over this period of time. To this end, the number of times their abstracts have been viewed can be used as a proxy to their reputation on RePEc.org. Note that we were not able to retrieve number of abstract views for 53 economists in our dataset.

- **Top 10%**[7]: represents whether the economists is ranked within top 10% authors on `RePEc.org`.

- **Affiliated institution**: This includes location of the affiliated institution, which consists of the country and the city. We have categorized the country fields according to the following two dummy variables:

  - *US Affiliation*: demonstrates whether the economist’s affiliated institution is located in the United States.

  - *English Affiliation*: demonstrates whether the economist’s affiliated institution is located in countries where English is a de jure / de facto official language[8].

- **# of Recommendations**: There are 6 English publications for each the economists in our main study dataset, and the system recommend a Wikipedia article for each publication. However, there are publications that, because of inappropriate profile on `RePEc.org`, the system was not able to recommend any Wikipedia article for. Table 4 shows the number of economists in our dataset with less than 6

[6] Access Statistics for Authors Registered in the RePEc Author Service
[7] Top 10% Authors, as of November 2016 (with details)
[8] List of territorial entities where English is an official language - Wikipedia

recommendations. For each publication in the dataset, their abstracts and NEP categorizations are retrieved from `https://ideas.repec.org/` and `http://econpapers.repec.org/`.

# of Recommendations	# of Economists
1	1
2	4
3	28
4	128
5	579
6	3,234
Total	3,974

Table 4: # of economists in the main study dataset and their # of recommendations.

6.1.2 Features of the Recommended Wikipedia Articles

In this study, 3,304 distinct Wikipedia articles have been recommended to the economists. For each Wikipedia article, the following features have been retrieved. Table 5 presents the summary statistics of these features.

Variable	# of Observations	Mean	Standard Deviation	Minimum	Maximum
Quality:[a]					
FA Class	3,304	.0548	.228	0	1
GA Class	3,304	.247	.431	0	1
B Class	3,304	.522	.5	0	1
C Class	3,304	.155	.362	0	1
Start	3,304	.016	.126	0	1
Stub	3,304	.00454	.0672	0	1
Importance:[b]					
Top Importance	3,304	.143	.351	0	1
High Importance	3,304	.284	.451	0	1
Mid Importance	3,304	.276	.447	0	1
Low Importance	3,304	.107	.309	0	1
Unclassified	3,304	.189	.392	0	1
Character Length	3,304	32,441	34,371	1,545	468,642
# of Watchers	3,304	64.2	93.7	0	1,065
# of Redirects	3,303	8.87	10.1	0	98
# of Total Edits	3,303	685	1,104	4	15,737
Past Month Views	3,304	12,993	23,609	77	615,420

Table 5: Features of the recommended Wikipedia articles summary statistics.

[a] There are four articles with no quality scale.
[b] Unclassified articles include ”Unknown-importance”, ”NA-importance”, and articles with no importance scale.

- **Quality scale**[9]: Probabilities of the article having each quality scale have been retrieved from the API

[9]Detailed explanation of Wikipedia quality scales is available at: Wikipedia:WikiProject Wikipedia/Assessment - Wikipedia.

provided by Yang et al. [43][10]. The quality scale for each Wikipedia article is identified using the weighted average of the possibilities retrieved. Quality scales in this study include FA, GA, B, C, and Start.[11]

- **Importance scale**[12]: retrieved from social tags assigned to the Talk page of each article. Importance scales in this study include Top-importance, High-importance, Mid-importance, Low-importance, and unclassified articles[13].

- **Character length**: MediaWiki measures the length of each Wikipedia article as the number of characters in the article[14].

- **# of Watchers**: shows the number of Wikipedia users who have added this article to their Watchlist[15].

- **# of Redirects**: represents the number of Wikipedia pages that automatically send visitors to this Wikipedia article[16].

- **# of Total Edits**: demonstrates the number of times this Wikipedia article has been edited[17].

- **Past Month Views**: indicates the number of times this Wikipedia article has been opened in a web browser over the past 30 days of the time we retrieved the data about this article[18].

- **Cosign Similarity**: Other than the above mentioned features of the Wikipedia article, we measured the quality of each recommendation by taking the Cosign similarity between the text content of the Wikipedia article and the abstract of the corresponding publication by the economist. For this purpose, first we entered both text files into a tokenizer [16], then each result was processed by a stemmer [1].

[10] `https://ores.wmflabs.org/scores/enwiki/wp10/<revisionID>`

[11] Note that as explained in algorithm 2, Stubs are not recommended to economists. However, a number of economists asked us to provide them with the commenting interface on specific Wikipedia articles, some of them classified as Stub or with no quality scale. So, there are few Stubs and four articles with no quality scale included in our dataset.

[12] Detailed explanation of Wikipedia importance scales is available at: Wikipedia:WikiProject Wikipedia/Assessment - Wikipedia.

[13] Unclassified articles include ”Unknown-importance”, ”NA-importance”, and articles with no importance scale.

[14] The character length of each Wikipedia article is retrieved from MediaWiki API.

[15] For more information refer to Help:Watchlist - Wikipedia. The number of watchers of each Wikipedia article is retrieved from MediaWiki API.

[16] For more information refer to Help:Redirect - Wikipedia. The number of redirects to each Wikipedia article is retrieved from MediaWiki API.

[17] For more information refer to Help:Redirect - Wikipedia. The number of edits of each Wikipedia article is retrieved from MediaWiki API.

[18] The number of views of each Wikipedia article is retrieved from `https://www.wikimedia.org/api/rest_v1/`.

	Average View No Private	Average View Citation	Average View Acknowledgment	High View No Private	High View Citation	High View Acknowledgment
Related Field	.0501	.0583	.061	.0456	.056	.0684
	(.218)	(.234)	(.24)	(.209)	(.23)	(.253)
Author Abstract Views	1,610	1,633	1,762	1,699	1,810	1,644
	(1,764)	(1,875)	(2,635)	(2,107)	(2,652)	(1,764)
Top 10%	.36	.378	.357	.347	.371	.386
	(.48)	(.485)	(.48)	(.477)	(.483)	(.487)
US Affiliation	.201	.214	.208	.255	.221	.193
	(.401)	(.41)	(.406)	(.436)	(.415)	(.395)
English Affiliation	.417	.457	.435	.453	.477	.407
	(.493)	(.499)	(.496)	(.498)	(.5)	(.492)
Observations	678	669	672	636	661	658

Table 6: Pre-treatment characteristics of economists, by conditions[a]

[a] Standard deviations are in parentheses.

Afterwards, the results were passed to a tf-idf vectorizer [35]. Finally the Cosign similarity [34] of the two vectors was calculated.

6.2 Randomization Check of the Treatment Assignments

We hypothesize that our experimental models extract causal effects from the data. For this purpose, we have assigned the control and treatment groups randomly. In order words, we hypothesize approximate equation of characteristics across groups. In order to test our hypothesis that the treatment model balanced the covariates, a balance check of the random treatment assignment is provided. The summary statistics are reported in Tables 6 and 7, broken down into the six experimental conditions. Table 6 demonstrates balance in the characteristics of the economists and table 7 shows balance in the features of the recommended Wikipedia articles among treatment and control conditions.

6.3 Incentives to Contribute to Wikipedia

Each economist who participates in this study makes sequential decisions throughout the experiment. These decision making processes are made in multiple phases of the study as follows:

1. **Phase 1**: Whether to participate in the study. This decision making yields one of the following three results:
   - Negative response,
   - No response,

	Average View No Private	Average View Citation	Average View Acknowledgment	High View No Private	High View Citation	High View Acknowledgment
Quality:[b]						
FA class	.0543	.0496	.0463	.0585	.0466	.0477
	(.227)	(.217)	(.21)	(.235)	(.211)	(.213)
GA class	.216	.211	.215	.226	.205	.2
	(.412)	(.408)	(.411)	(.418)	(.404)	(.4)
B class	.594	.604	.601	.581	.613	.613
	(.491)	(.489)	(.49)	(.493)	(.487)	(.487)
C class	.127	.125	.126	.123	.122	.128
	(.333)	(.331)	(.332)	(.328)	(.328)	(.334)
Start	.00714	.00801	.0104	.01	.0116	.0103
	(.842)	(.0891)	(.101)	(.0996)	(.107)	(.101)
Stub	.00178	.00181	.00104	.0019	.00132	.000527
	(.0422)	(.0425)	(.0322)	(.0435)	(.0364)	(.023)
Importance:						
Top importance	.168	.16	.158	.173	.152	.153
	(.374)	(.367)	(.365)	(.378)	(.359)	(.36)
High importance	.35	.339	.353	.347	.358	.348
	(.477)	(.474)	(.478)	(.476)	(.48)	(.476)
Mid importance	.255	.27	.256	.245	.264	.263
	(.436)	(.444)	(.437)	(.43)	(.441)	(.44)
Low importance	.064	.0731	.0702	.0674	.0675	.0712
	(.245)	(.26)	(.256)	(.251)	(.251)	(.257)
Unclassified	.162	.157	.162	.168	.158	.166
	(.369)	(.364)	(.368)	(.374)	(.365)	(.372)
Character Length	34,266	33,973	34,579	36,269	35,000	34,122
	(33,553)	(33,195)	(34,269)	(36,399)	(34,875)	(33,566)
# of Watchers	82	80.2	79.8	83.1	83.7	80.7
	(102)	(107)	(105)	(108)	(107)	(106)
# of Redirects	9.13	8.87	8.85	9.33	9.29	8.85
	(9.34)	(9.54)	(9.24)	(10)	(9.79)	(9.19)
# of Total Edits	725	725	708	754	750	711
	(997)	(1,081)	(1,003)	(1,066)	(1,102)	(1,035)
Past Month Views	14,409	14,023	14,013	14,348	14,471	13,917
	(17,086)	(19,842)	(19,956)	(18,108)	(19,955)	(21,379)
Cosine similarity	.141	.142	.142	.145	.141	.142
	(.101)	(.1)	(.102)	(.101)	(.0986)	(.102)
Observations	3,924	3,872	3,845	3,693	3,779	3,794

Table 7: Pre-treatment features of the recommended articles, by conditions[a]

[a] Standard deviations are in parentheses.
[b] There are four articles with no quality scale.

- Positive response.

2. **Phase 2**: In case of a positive response in phase 1, there are multiple decision making processes involved in the second phase:

   (a) Whether to open the review interface of each of the recommended Wikipedia articles. This decision making yields a dichotomous (Yes/No) result.

   (b) In case of a positive decision in the previous step, how much to comment on the Wikipedia article.

Each of the above mentioned decision making processes are analyzed separately in the following subsections.

Note that throughout the analysis, we have used both BIC (Schwarz et al. [33]' Bayesian Information Criterion) and AIC (Akaike [2]'s Information Criterion) for model selection. As a result, in comparison between two models that characterize the same outcome, we have chosen the one with smaller values of both AIC and BIC.

6.4 Phase 1: Incentives to Participate

We first investigate the factors that incentivize economists to participate in this study. For this purpose, our system tracks the emails sent to the economists, and in our analysis we only consider those who open the first phase emails and are exposed to the treatments. Our rationale for this restriction is that before opening the emails, the economists only see the subject lines of the emails that include their recent fields of research (domains of expertise), but nothing about the treatments is mentioned in the subject lines. To this end, only among those who open the emails, we explore what motivates them to:

- Click the "Yes" link in our emails that indicates their willingness to receive our recommended Wikipedia articles to contribute to.

- Ignore our email after opening it and do not respond, nor click any of the links in the email. In such a case, we assume they postpone responding to a later time and the system sends them a reminder email in two weeks. If they do not respond again in two weeks, the system repeats sending reminders for four times. So, only those economists remain in this category who have opened the first phase email and have not responded nor clicked any of the links even after receiving the four reminders.

Table 8: Average Marginal Effects of Multinomial logistic regression on participation.[a]

	Negative Response	No Response	Positive Response
Related Field	-.135***	-.0752***	.210***
	(.0251)	(.0282)	(.0337)
High View (Public Benefit)	-.0262*	.00745	.0188
	(.0151)	(.0152)	(.0173)
Citation Benefit	-.0628***	.0138	.0490**
	(.0186)	(.0185)	(.0211)
Acknowledgment Benefit	-.0515***	.0208	.0307
	(.0188)	(.0186)	(.0212)
Author Abstract Views[b]	.384***	-.417**	.0328
	(.145)	(.192)	(.188)
English Affiliation	.0604***	-.0435***	-.0170
	(.0154)	(.0159)	(.0175)

[a] Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

[b] Author Abstract Views is linearly normalized to range [0, 1]. The original values were in range [51, 46,057].

- Click the ”No” link in our emails that indicates opting out of the study.

Table 8 shows the margins of a multinomial logit regression of effects of the economists' characteristics and treatment conditions on their responses to our first invitation email. Since ”Top 10%” already represented by ”Author Abstract Views” and ”US Affiliation” is already represented by ”English Affiliation”, including ”Top 10%” or ”US Affiliation” decreases the fitness of the model and increases both AIC and BIC of the model. So we did not include these two covariates in our model. Furthermore, the interactions between the treatment factors have been included in the regression model and marginal effects of each covariate is reported. Nevertheless, an ANOVA Chi^2 test comparing the two nested models show that interactions between the public and private benefits do not have a significant effect on the model and including the interactions does not affect the model. Moreover, adding the interaction of the treatment factors in the model increase both AIC and BIC and results in a less fit model. To this end, the regression model is characterized in the equation 1:

$$\begin{aligned} Response_i = \beta_0 + \beta_1 HighView_i + \beta_2 Citation_i + \beta_3 Acknowledgement_i + \\ \beta_4 RelatedField_i + \beta_5 AbstractViews_i + \beta_6 EnglishAffiliation_i + \epsilon_i \end{aligned} \tag{1}$$

In table 8, among the treatment conditions, we observe those economists who are exposed to the high view (public benefit), citation benefit, or acknowledgment benefits are less likely to respond negatively to our emails, by 2.6%, 6.3%, and 5.1% respectively. More interestingly, those who are exposed to the citation benefit respond positively 4.9% more than others. Also, those with an affiliation from a country in which English is a formal language are 4.3% less likely to ignore our emails, though they are 6.0% more likely to respond negatively.

In terms of the numeric variable, the number of times the economists' abstracts have been viewed on `RePEc.org` over the year 2016, the average marginal effects represent the "instantaneous rate of change" [6, 25]. I.e., we cannot predict the effect of a large increase in this covariate on the outcome variable. This is because the relationship between the covariate and the probability of positive/negative/no response is not necessarily linear. To this end, we use the method suggested by Cameron and Trivedi [6], Long and Freese [25] and conclude that 1,000 increase in the number of times the economist's abstracts have been viewed on RePEc.org over the year 2016, is significantly correlated with .91% decrease in the likelihood of not responding to our emails. At the same time, it is significantly correlated with .83% increase in the likelihood of negatively responding to our invitation.

More importantly, those with the most recent field of research, domain of expertise, the same as one of the authors of the paper who has signed the emails to economists, significantly respond to our invitation emails by 7.52% more than others. At the same time, they significantly respond to our emails by 13.5% less negatively and 21% more positively in comparison with other economists in this study. This finding is aligned with Algan et al. [3], which show that reciprocity and social image are both strong motives for sustaining cooperation in peer production environments, while altruism is not. Nevertheless, while Algan et al. [3] studied members of Wikipedia, we observed a similar behavior among non-members (economists). Following this result, we hypothesize that those in related fields might have a different attitude towards the treatment conditions. In order to test this hypothesis, we separate them from other economists and analyze their responses in two separate models demonstrated in table 9. Results indicate that while exposure to high view or citation benefit conditions do not affect responses of those in related fields, other economists consider the citation benefit more significantly than those in related fields. All economists who responded to our emails, consider the acknowledgment benefit significantly, though in the opposite direction. Detailed explanation of findings is as follows:

- **Those in related fields**: It is surprising that those who are exposed to the acknowledgment benefit are 17.5% less likely to respond positively to our invitations. Other factors do not have any significant effect on responses from economists in related fields.

Table 9: Average Marginal Effects of Multinomial logistic regressions on participation, in subset analysis separated by related field.[a]

	Not In Related Field			**In Related Field**		
	Negative Response	**No Response**	**Positive Response**	**Negative Response**	**No Response**	**Positive Response**
Public Benefit	-.0220	.00635	.0156	-.0865	.0217	.0648
	(.0158)	(.0158)	(.0179)	(.0462)	(.0536)	(.0636)
Citation Benefit	-.0681***	.0154	.0527**	.0326	-.00472	-.0279
	(.0195)	(.0193)	(.0219)	(.0521)	(.0640)	(.0759)
Acknowledgment Benefit	-.0607***	.0170	.0437*	.0986	.0766	-.175**
	(.0197)	(.0193)	(.0219)	(.0553)	(.0660)	(.0772)
Author Abstract Views[b]	.402**	-.459**	.0571	.170	.353	-.523
	(.151)	(.201)	(.193)	(.577)	(.687)	(.819)
English Affiliation	.0670***	-.0425**	-.0245	-.0367	-.0751	.112
	(.0162)	(.0160)	(.0182)	(.0460)	(.0539)	(.0639)

[a] Standard errors are in parentheses.
P-values are Bonferroni adjusted $^{*}p<0.05$; $^{**}p<0.025$; $^{***}p<0.005$

[b] Author Abstract Views is linearly normalized to range [0, 1]. The original values were in range [51, 46,057].

- **Other Economists**: Those who are exposed to any private benefit (citation or acknowledgment) are 6.81% and 6.07% less likely to respond negatively. Correspondingly, they are 5.27% and 4.37% more likely to respond positively. In terms of economists' reputation on `RePEc.org`, every 1,000 increase in their number of abstract views over 2016 is correlated with 1% less ignorance of our emails, but .87% more negative response. More interestingly, those affiliated with institutions in countries with English as a formal language are 4.25% less likely to ignore our emails, but they tend to respond more negatively by 6.7%.

6.5 Phase 2: Incentives to Contribute

Linear Mixed Models are statistical models which assume normal distribution of residuals, but do not assume independence nor constant variance [39]. These models are linear in the parameters, and allow the covariates (independent variables) to involve both fixed and random effects.

In LMM, fixed effects are considered as unknown constant parameters corresponding to continuous or categorical covariates. In corresponding linear regression models, fixed effects are known as regression coefficients. Since they measure the relationships between the covariates and the outcome variable, their estimation is the main focus of LMMs. On the other hand, random effects in LMMS are defined as effects associated with levels of categorical variables that can be considered samples from a sample space, the focus of the model is not on each particular level. As opposed to fixed effects, LMMs represent random effects by (unobserved) random variables, with a usual assumption of normality in distribution [39]. One of the applications of LMMs is to analyze models with crossed random factors, which characterize multiple random factors that in the same model are crossed with each other.

Figure 1 demonstrates boxplot of the number of words each recommended Wikipedia article has received among those Wikipedia articles that have been recommended for more than 100 times. We clearly observe variations in mean and variance of number of words commented on different articles. This suggests heteroscedasticity between comments received by each Wikipedia article that indicates random effects of each article on participation to it. On the other hand, figure 2 demonstrates boxplot of the number of words each participant has contributed through this study, among positive contributions of randomly selected 250 participants in the study. Again, we observe variations in mean and variance of number of words commented by different participants in this study among the six recommendations that we have provided for them. Note that as we discussed in the previous section, there are participants who received less than six recommendations. This suggests heteroscedasticity between comments provided by each participants that indicates random effects of each participant on participation to this study. To this end, both of the participants and the recommended Wikipedia articles have multiple measures on the dependent variable associated with them, but the levels of these two random factors (economist ID and Wikipedia article ID) are crossed with each other. In other words, there is heterogeneity across individuals and across recommended Wikipedia articles in the effect of contributing to the Wikipedia articles. So we have ”alternative-variant” or ”alternative-specific” regressors, i.e., the observed effects vary over the economists and the recommended Wikipedia articles. ”LMMs with crossed random effects enable the potential correlations of the repeated observations associated with each level of these crossed random factors to be modeled simultaneously.” [39] For example, we might expect between-economist variance in contribution to Wikipedia; at the same time, we might expect that some Wikipedia articles are intrinsically more interesting to comment on, resulting in between-article variance in the contribution. ”These models enable simultaneous estimation of the components of variance associated with the levels of the crossed random factors, and assessment of which random factor tends to contribute the most to variability in measures on the dependent variable.” [39] On the other hand, because each participant in this study has received up to 6 recommended Wikipedia articles, some of the popular Wikipedia articles are recommended to multiple economists. Figure 3 demonstrates number of times each Wikipedia article in our dataset is recommended to different economists. As a result, there might be multiple levels of potentially correlated observations in the dataset. LMMs including random effects for both of the economists and recommended Wikipedia articles enable decomposition of the components of variance due to each of these crossed random factors.

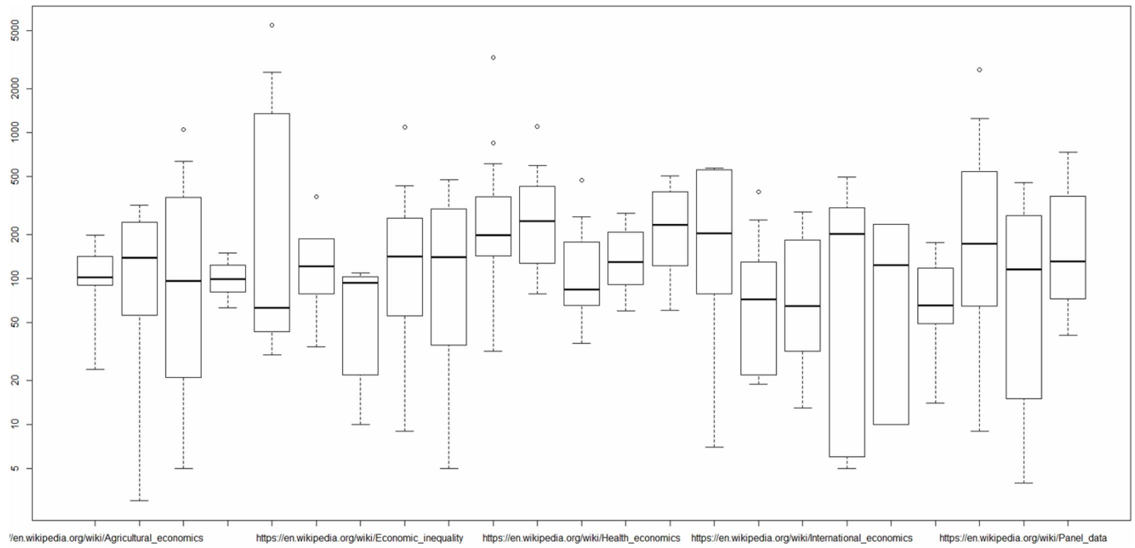


Figure 1: Boxplot of the number of words each recommended Wikipedia article has received among those Wikipedia articles that have been recommended for more than 100 times.

Table 10 shows the odds ratios of linear mixed models with logistic distribution of effects of the economists' characteristics, treatment conditions, and recommended Wikipedia articles' features on their choice of Wikipedia articles recommended to them. I.e., among the six Wikipedia articles recommended to each economist, which articles they click and enter the reviewing interface. With a similar rationale as discussed in the phase 1, we have reported the subset analysis of the results based on whether the participant is in related field. In addition, we only include "Related Field", "Author Abstract Views", and "English Affiliation" in the model. Furthermore, including the interactions between the treatment factors significantly increase both AIC and BIC, such that by including the interaction covariates the maximum likelihood estimators of the linear mixed model do not converge. On the other hand, since in this phase of the study participants are exposed to the titles of the recommended Wikipedia articles in their personalized list of recommendations, we insert features of the Wikipedia articles in our LMMs. These characteristics include:

- **ViewsScaled**: Number of times the articles has been viewed over the past month. This variable demonstrates the popularity of the article among readers. Note that the original values of this variable are in range [77, 615,420]. The values are normalized to range [0, 1] before being entered in the LMMs. Note that those participants under the HighView condition are exposed to the original number

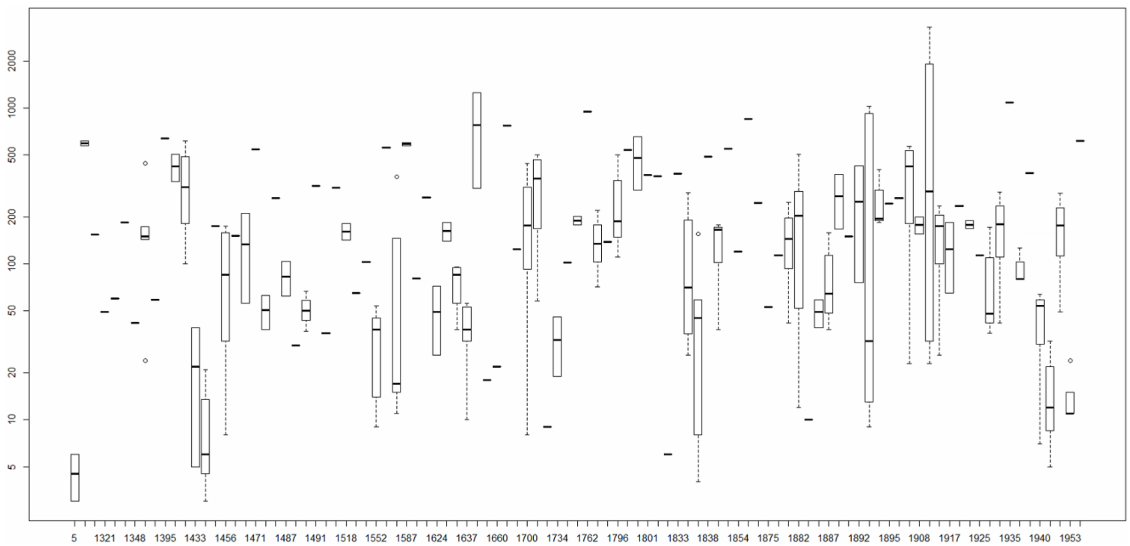


Figure 2: Boxplot of the number of words each participant has contributed through this study, among positive contributions of randomly selected 250 participants in the study.

of views of each recommended Wikipedia article in their recommendations list (Figure 18). So, we consider the interaction between HighView condition and ViewsScaled in the LMMS.

- **EditsNumberScaled**: This factor represents the popularity of the recommended Wikipedia article among Wikipedians (Wikipedia editors). This variable is normalized to the range [0, 1]. Note that the original values of this variable are in range [4, 15,737].

- **RecommendationRepetitionScaled**: This factor represents the number of participants this Wikipedia article has been recommended to. It can be considered as a proxy of the popularity of the recommended Wikipedia article among economists. This variable is normalized to the range [0, 1]. Note that the original values of this variable are in range [1, 346].

- **CosignSimilarity**: This factor is entered as a proxy of the quality of each recommendation in the list of recommendations. I.e., it indicated how related each recommended Wikipedia article is to the corresponding publications of the participant. This variable takes values in range [-1, 1].

The linear mixed model is characterized in the equation 2. In this model, covariates $Expert_i$ and $Wikipage_j$ indicate random effects of participant i and recommended Wikipedia article j respectively. The outcome variable in this model represents whether participant i has clicked the link to the review page of Wikipedia article j.

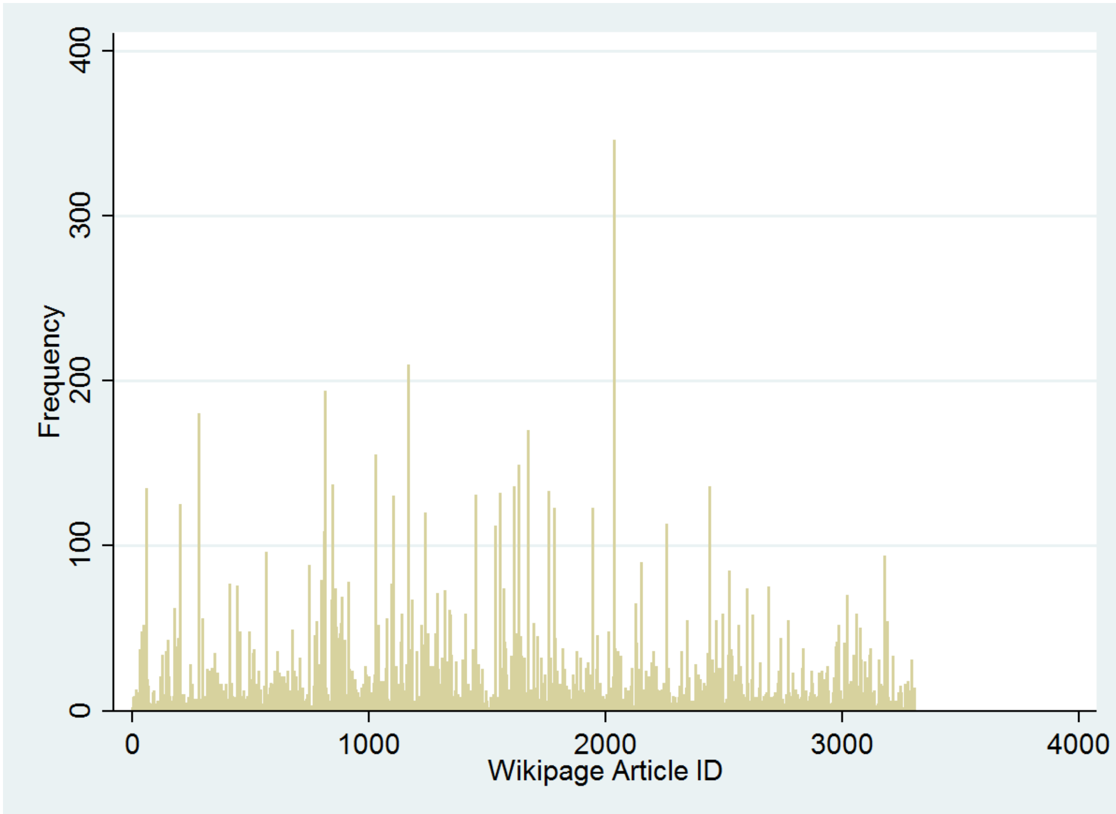


Figure 3: Histogram of the number of times each Wikipedia article has been recommended to different economists.

$$
\begin{aligned}
LinkClicked_i = \beta_0 + \beta_1 HighView_i + \beta_2 ViewsScaled_j + \beta_3 HighView_i * ViewsScaled_j + \\
\beta_4 Citation_i + \beta_5 Acknowledgement_i + \beta_6 CosignSimilarity_i + \\
\beta_7 EditsNumberScaled_j + \beta_8 RecommendationRepetitionScaled_j + \\
\beta_1 0 RelatedField_i + \beta_1 1 AbstractViewsScaled_i + \beta_1 2 EnglishAffiliation_i + \\
Expert_i + Wikipage_j + \epsilon_i j
\end{aligned} \tag{2}
$$

In table 10, among the treatment conditions, we observe that the high view (public benefit), citation benefit, or acknowledgment benefits do not have any significant effect on choosing Wikipedia articles. On the other hand, those participants in the high view condition have already learned about the fact that the recommended Wikipedia articles have been viewed more than 1,000 times over the past month and being exposed to the actual number of views of each recommended Wikipedia article does not have any significant effect on their choice of the article. More importantly, higher cosign similarity between the recommended article content and the abstract of the corresponding publication is significantly correlated with the participants' willingness to chose the corresponding Wikipedia article. I.e., economists prefer to chose articles that are more related to their recent publications. It is also interesting that economists have a tendency toward topics that are more popular among economists. In other words, they click the Wikipedia articles that are recommended to many economists significantly more than others. This might be due to the fact that popular articles are about the more general topics that makes them easier to edit.

As opposed to the first phase, being in related field does not significantly affect link clicks. However, similar to the first phase, those in related fields behave differently in comparison to others. The detailed comparison between the two groups is as follows.

- **Those in related fields**: It is surprising that those who are exposed to the number of views of each recommendation over the past month do not significantly behave differently from others. However, not knowing the number of views and having no information about the popularity of the articles, economists in the related fields click the articles that are not popular among readers significantly more than the popular articles.

- **Other Economists**: We observe a tendency toward clicking articles that are less popular among Wikipedians, i.e., articles with less number of edits. This finding is very surprising because at this phase participants are not exposed to the content of the Wikipedia articles and do not know the quality or length of the content yet. In addition, those economists from countries in which English is an official language tend to click on less recommendations in comparison with others.

6.6 Phase 2: How much to Contribute

As discussed in the previous section, we need to consider random effects of different Wikipedia articles and participants as crossed section effects on contribution to Wikipedia. Table 11 shows the odds ratios of linear mixed models with Zero-inflated Negative Binomial distribution of effects of the economists' characteristics, treatment conditions, and recommended Wikipedia article features on the number of words they commented on each Wikipedia article recommended to them. I.e., how much comment they provide for each of the Wikipedia articles that they have chosen. It is noteworthy to mention that among chosen (clicked) Wikipedia articles, 67.58% of the recommendations receive no comments, meaning that the participant opens the link, but then decides not to comment on the article. Figure 4 demonstrates a scatter plot of number of words contributed to each chosen recommended Wikipedia article in log scale by the consign similarity between that Wikipedia article and corresponding publication by the participant. This diagram clearly visualizes two groups of chosen recommendations: 67.58% of them have not received any comment, but when a participant contributes, they contribute a significant amount. This is because commenting on an article requires a significant amount of time to read the article and we ask the participants to comment on at least one of the recommended Wikipedia articles. So in the first step, based on the title of the articles, they choose and open a number of them. in the second step, they choose the most interesting articles to comment on. As a result, after choosing a specific article and spending some time to read it, the participant provides a significant amount of comment on the article, because the marginal cost of starting to edit is much larger than the cost of editing. I.e., the participants do not comment on the recommended Wikipedia articles, but when they contribute, they enter a significant number of words. To this end, we argue that the underlying distribution of zero and positive contribution is different and it is not possible to analyze the results using standard count models or a Tobit model. On the other hand, even after deciding to read and comment on a Wikipedia article, the participant might end up with nothing to comment on. So, it is not possible to use a Hurdle (Craggs) model. Hence, the most appropriate family of models that fit the characteristics of this phase is zero-inflated count models. Between zero-inflated Poisson and negative binomial models, because of over-dispersion in the distribution, it is not practical to use a Zero-inflated Poisson model and the only appropriate model to explain the data in this phase is a linear mixed model with an underlying Zero-inflated negative binomial distribution.

As oppose to the previous two phases, being in related field has no significant effect on the amount of contribution. Figure 5 demonstrates boxplots of the cumulative number of words contributed by participants in each domain of expertise. In addition, there are only 116 participants in related fields who have clicked on at least one recommendation link. So, in this phase, we do not provide a subset analysis. Furthermore, including the interactions between the treatment factors significantly increase both AIC and BIC, such that by including the interaction covariates the maximum likelihood estimators of the linear mixed model do not converge. On the other hand, since in this phase of the study participants are exposed to the content of the recommended Wikipedia articles through the review interface, we insert features of the Wikipedia articles in our LMMs. These characteristics include:

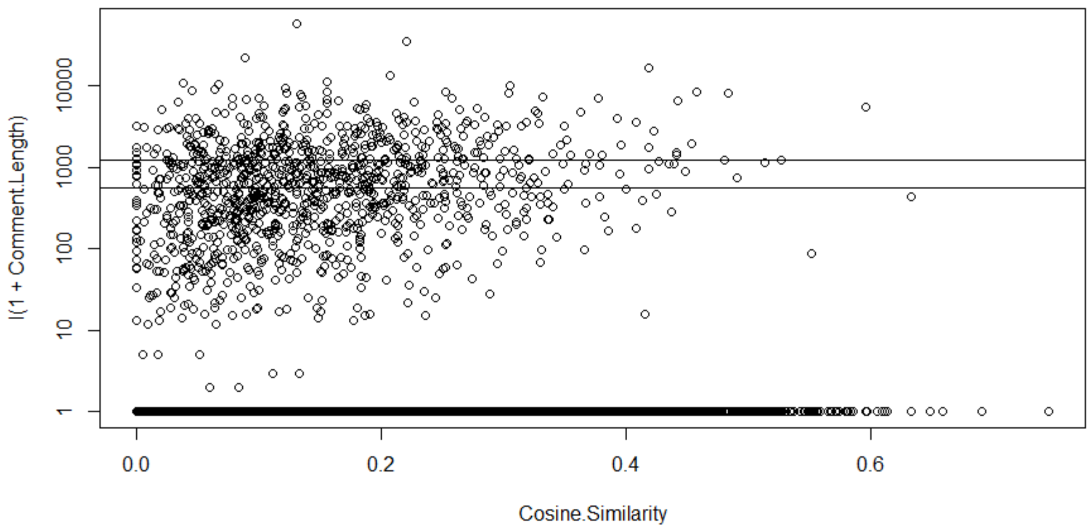


Figure 4: Scatter plot of number of words contributed to each chosen recommended Wikipedia article by the consign similarity between that Wikipedia article and corresponding publication by the participant.

- **ViewsScaled**: Number of times the articles has been viewed over the past month. This variable demonstrates the popularity of the article among readers. Note that the original values of this variable are in range [77, 615,420]. The values are normalized to range [0, 1] before being entered in the LMMs. Note that those participants under the HighView condition are exposed to the original number of views of each recommended Wikipedia article in their recommendations list (Figure 18). So, we consider the interaction between HighView condition and ViewsScaled in the LMMS.

- **EditsNumberScaled**: This factor represents the popularity of the recommended Wikipedia article among Wikipedians (Wikipedia editors). This variable is normalized to the range [0, 1]. Note that the original values of this variable are in range [4, 15,737].

- **RecommendationRepetitionScaled**: This factor represents the number of participants this Wikipedia article has been recommended to. It can be considered as a proxy of the popularity of the recommended Wikipedia article among economists. This variable is normalized to the range [0, 1]. Note that the original values of this variable are in range [1, 346].

- **CosignSimilarity**: This factor is entered as a proxy of the quality of each recommendation in the list of recommendations. I.e., it indicated how related each recommended Wikipedia article is to the corresponding publications of the participant. This variable takes values in range [-1, 1].

- **PageLengthScaled**: This factor represents the number of characters in content of each Wikipedia article. This variable is normalized to the range [0, 1]. Note that the original values of this variable are in range [1,545, 468,642].

The linear mixed model is characterized in the equation 3. In this model, covariates $Expert_i$ and $Wikipage_j$ indicate random effects of participant i and recommended Wikipedia article j respectively. The outcome variable in this model represents the number of words participant i has commented on Wikipedia article j.

$$\begin{aligned} Word - Count_i = \beta_0 + \beta_1 HighView_i + \beta_2 ViewsScaled_j + \beta_3 HighView_i * ViewsScaled_j + \\ \beta_4 Citation_i + \beta_5 Acknowledgement_i + \beta_6 CosignSimilarity_i + \\ \beta_7 EditsNumberScaled_j + \beta_8 RecommendationRepetitionScaled_j + \beta_1 0 PageLengthScaled_j + \\ \beta_1 1 RelatedField_i + \beta_1 2 AbstractViewsScaled_i + \beta_1 3 EnglishAffiliation_i + \\ Expert_i + Wikipage_j + \epsilon_i j \end{aligned} \tag{3}$$

In table 10, among the treatment conditions, we observe that while the high view (public benefit) and citation benefits do not have any significant effect on choosing Wikipedia articles, being under acknowledgment benefit, participants contribute significantly more than others. This aligned with CEM's second recommendation. When we inform the participants that their contribution will be identifiable though listing their names and their contribution in the list of economists on the Economics Wikiproject, they tend to contribute significantly more than others. On the other hand, those participants in the high view condition have already learned about the fact that the recommended Wikipedia articles have been viewed more than 1,000 times over the past month and being exposed to the actual number of views of each recommended Wikipedia article does not have any significant effect on their choice of the article. However, not knowing the number of views and having no information about the popularity of the articles, participants comment on the articles that are not popular among readers significantly more than the popular articles. More importantly, higher cosign similarity between the recommended article content and the abstract of the corresponding publication is significantly correlated with the participants' amount of comment on the corresponding Wikipedia article. I.e., economists prefer to comment more on articles that are more related to their recent publications. It is also interesting that economists have a tendency toward topics that are more popular among economists. In other words, they comment on Wikipedia articles that are recommended to many economists significantly more than others. This might be due to the fact that popular articles are about the more general topics that makes them easier to edit.

7 Conclusion

By conducting a 2-phase online field experiment on Wikipedia, we investigate how to motivate domain experts, economists in this study, to contribute to Wikipedia. The results of the first phase reveal that sending invitation emails to economists mentioning their recent fields of research in the subject line of the emails motivates them to open their emails. In addition, sending the invitation emails from another expert in the same field of research and having them sign the invitation emails, significantly incentivizes domain experts to respond positively to the invitation emails. Also, making the experts aware of the private benefits that they might gain from contributing to Wikipedia, such as likelihood of their publications being cited, significantly increases their positive response to contribute. On the other hand, while informing them about identification of their contribution on Wikiprojects increases positive response and decreases negative response from those in unrelated domains of expertise, it significantly decreases positive response from experts in related fields. Moreover, highly reputable economists in unrelated fields respond their invitation emails more than others though negatively. Similarly, inviting economists in unrelated fields who are affiliated with institutions in countries in which English is a formal language, to edit English Wikipedia articles, results in receiving more response though significantly more negative.

The results of the second phase of this study demonstrate a tendency toward contributing to Wikipedia articles that are more related to the experts' recent publications, and have been more popular among domain experts, in the sense that have been recommended to many economists. More importantly, making economists aware of the fact that their contributions will be identified in a list of economist contributors on Wikiproject Economics significantly increases their amount of contribution. Finally and more importantly, economists show a tendency toward contributing to articles that have been less popular among readers when they are not aware of this popularity.

8 Appendix

Table 10: Linear Mixed Models with logistic distribution of Wikipedia Article Choice, subgroup analysis.

	Dependent variable:		
	Link Clicked		
	Overall	Not Related	Related
High View	-0.003	-0.058	0.610
	(0.112)	(0.117)	(0.414)
Views Scaled	1.202	2.345	-18.583^{**}
	(1.725)	(1.865)	(8.659)
Citation Factor	0.178	0.178	0.098
	(0.129)	(0.133)	(0.481)
Acknowledgement	0.149	0.166	-0.188
	(0.129)	(0.134)	(0.494)
Cosine Similarity	3.364^{***}	3.448^{***}	2.487^{**}
	(0.306)	(0.315)	(1.236)
Recommendation Repetition Scaled	0.617^{***}	0.400^{*}	2.117^{***}
	(0.212)	(0.214)	(0.516)
Total Edits Scaled	-0.969	-1.104^{*}	1.556
	(0.635)	(0.657)	(2.726)
Related Field	0.304		
	(0.186)		
Author Abstract Views Scaled	0.757	1.058	-5.016
	(1.040)	(1.059)	(4.986)
From English Language Country	-0.121	-0.183^{*}	0.622
	(0.105)	(0.109)	(0.395)
High View * Views Scaled	-1.062	-1.572	8.790
	(1.796)	(1.895)	(9.004)
Constant	-1.096^{***}	-1.057^{***}	-1.072^{**}
	(0.132)	(0.135)	(0.486)
Observations	8,558	7,799	759
Akaike Inf. Crit.	10,185.330	9,288.185	892.115
Bayesian Inf. Crit.	10,284.100	9,378.688	952.331

Note: Odds ratios are reported. *p<0.1; **p<0.05; ***p<0.01

Author Abstract Views is linearly normalized to [0, 1]. The original values were in [51, 46,057].

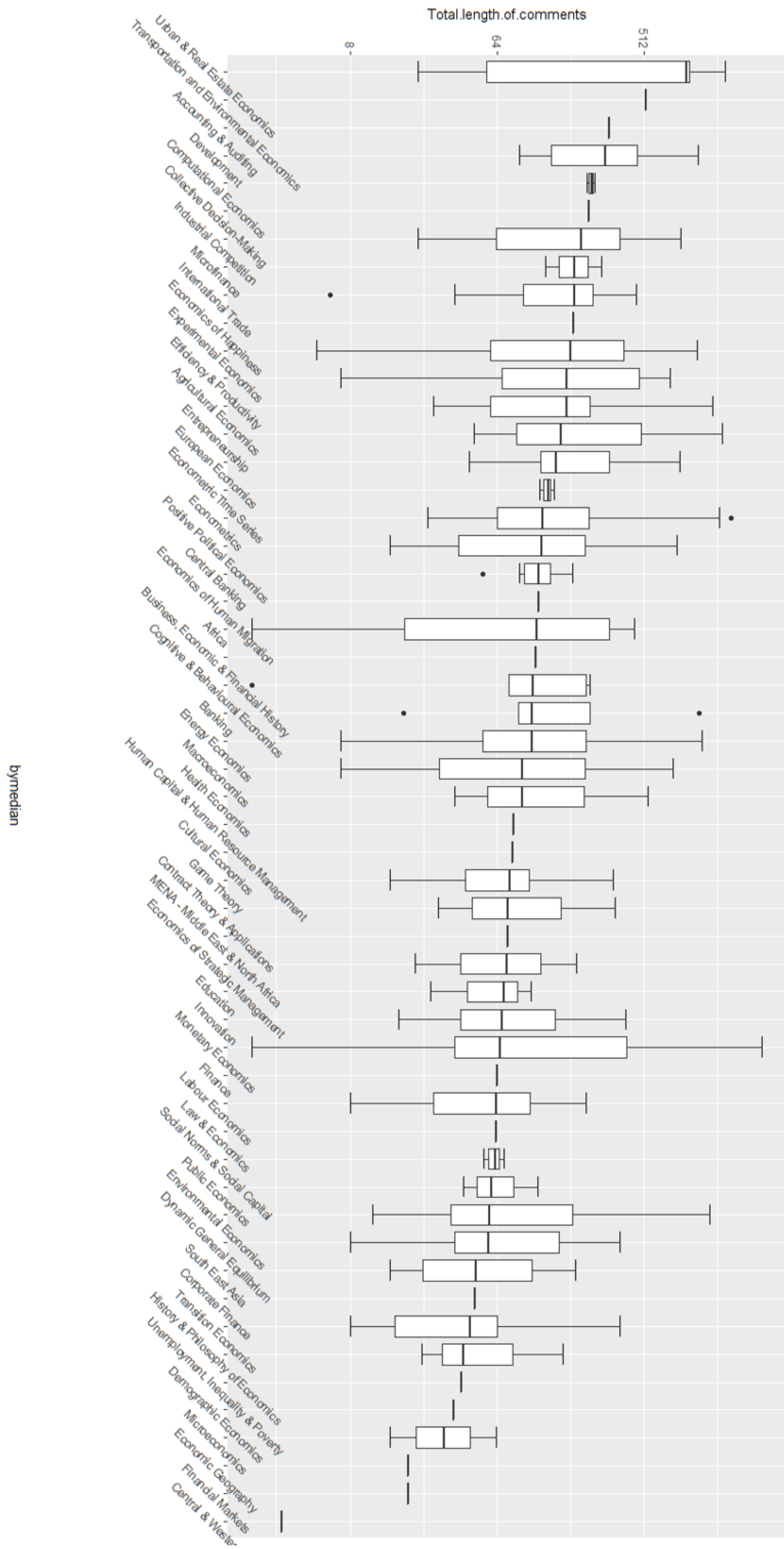


Figure 5: Cumulative number of Words contributed per Domain of expertise.

Table 11: Linear Mixed Models of Word-count of contribution with Zero-inflated Negative Binomial.

	Word-count
High View	-0.0523
	(0.1361)
Views Scaled	-2.8462^{**}
	(1.2396)
Citation Factor	-43.6879
	(9021.2000)
Acknowledgement	0.3016^{**}
	(0.1222)
Cosine Similarity	1.7554^{***}
	(0.4297)
Recommendation Repetition Scaled	0.6171^{**}
	(0.2603)
Page Length Scaled	0.7010
	(0.8438)
Total Edits Scaled	0.2670
	(1.1382)
Author Abstract Views Scaled	-0.2044
	(1.1268)
From English Language Country	0.0257
	(0.1217)
Related Field	-0.0903
	(0.2013)
High View * Views Scaled	1.4646
	(2.8187)
Constant	-7.212^{***}
	(0.513)
Observations	3,557
Akaike Inf. Crit.	26,445.8
dispersion parameter	1.3845 (std. err.: 0.10788)
Zero-inflation	0.65721 (std. err.: 0.0099902)
Note:	*p<0.1; **p<0.05; ***p<0.01

Domains of expertise	# of economists	Percent	Cumulative
Accounting and Auditing	6	0.15	0.15
Africa	81	2.04	2.19
Agricultural Economics	163	4.10	6.29
Bank Efficiency	1	0.03	6.32
Banking	76	1.91	8.23
Business Economics	25	0.63	8.86
Business, Economic and Financial History	56	1.41	10.27
Central and South America	9	0.23	10.49
Central and Western Asia	19	0.48	10.97
Central Banking	121	3.04	14.02
Chinese labor	1	0.03	14.04
Cognitive and Behavioural Economics	44	1.11	15.15
Collective Decision-Making	20	0.50	15.65
Computational Economics	23	0.58	16.23
Confederation of Independent States	4	0.10	16.33
Contract Theory and Applications	24	0.60	16.94
Corporate Finance	6	0.15	17.09
Cultural Economics	2	0.05	17.14
Demographic Economics	7	0.18	17.31
Development	110	2.77	20.08
Development Economics	1	0.03	20.11
Discrete Choice Models	5	0.13	20.23
Dynamic General Equilibrium	137	3.45	23.68
Econometric Time Series	17	0.43	24.11
Econometrics	184	4.63	28.74
Economic Geography	40	1.01	29.74
Economic Growth	1	0.03	29.77
Economics of Aging	17	0.43V30.20	
Economics of Happiness	9	0.23	30.42
Economics of Human Migration	48	1.21	31.63
Economics of Strategic Management	23	0.58	32.21
Economy of Turkey	1	0.03	32.23
Education	35	0.88	33.12
Efficiency and Productivity	60	1.51	34.63
Energy Economics	128	3.22	37.85
Entrepreneurship	45	1.13	38.98
Environmental Economics	148	3.72	42.70
European Economics	31	0.78	43.48
Evolutionary Economics	1	0.03	43.51
Experimental Economics	181	4.55	48.06
Finance	12	0.30	48.36
Financial Development and Growth	4	0.10	48.47
Financial Markets	8	0.20	48.67
Forecasting	17	0.43	49.09
Game Theory	70	1.76	50.86

Table 12: Domains of expertise retrieved and their corresponding number of economists contacted in our main study..

Domains of expertise	# of economists	Percent	Cumulative
Health Economics	62	1.56	52.42
History and Philosophy of Economics	14	0.35	52.77
Human Capital and Human Resource Manage...	5	0.13	52.89
Income and Wealth Distribution, Econo...	1	0.03	52.92
Industrial Competition	98	2.47	55.39
Information and Communication Technolog...	2	0.05	55.44
Innovation	83	2.09	57.52
Insurance Economics	6	0.15	57.67
International Finance	21	0.53	58.20
International Trade	139	3.50	61.70
Knowledge Management and Knowledge Econ...	1	0.03	61.73
Labour Economics	350	8.81	70.53
Law and Economics	19	0.48	71.01
MENA - Middle East and North Africa	26	0.65	71.67
Macroeconomics	490	12.33	84.00
Market Microstructure	8	0.20	84.20
Marketing	5	0.13	84.32
Microeconomic European Issues	3	0.08	84.40
Microeconomics	18	0.45	84.85
Microfinance	8	0.20	85.05
Monetary Economics	54	1.36	86.41
Network Economics	10	0.25	86.66
Open Economy Macroeconomics	13	0.33	86.99
Operations Research	1	0.03	87.02
Positive Political Economics	42	1.06	88.07
Post Keynesian Economics	7	0.18	88.25
Project, Program and Portfolio Management	1	0.03	88.27
Public Economics	71	1.79	90.06
Public Finance	1	0.03	90.09
Regulation	9	0.23	90.31
Risk Management	16	0.40	90.71
Small Business Management	5	0.13	90.84
Social Norms and Social Capital	14	0.35	91.19
Sociology of Economics	3	0.08	91.27
South East Asia	78	1.96	93.23
Sports and Economics	11	0.28	93.51
Tourism Economics	4	0.10	93.61
Transition Economics	85	2.14	95.75
Transport Economics	4	0.10	95.85
Transportation and Environmental Econ...	1	0.03	95.87
Unemployment, Inequality and Poverty	32	0.81	96.68
Urban and Real Estate Economics	118	2.97	99.65
Utility Models and Prospect Theory	13	0.33	99.97
probability and statistics	1	0.03	100.00
Total	3,974	100.00	

Table 13: Domains of expertise retrieved and their corresponding number of economists contacted in our main study..

Subject's Field of Expertise

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen, Last name

Title

Subject's Field of Expertise

Would you be willing to spend 10 - 20 minutes providing feedback on a few Wikipedia articles related to behavioral and experimental economics? Wikipedia is among the most important information sources the general public uses to find out about a wide range of topics. While many Wikipedia articles are useful, articles written by enthusiasts instead of experts can be inaccurate, incomplete, or out of date.

If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise.

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

If you would rather comment on articles in another area, please reply to this email and let us know.

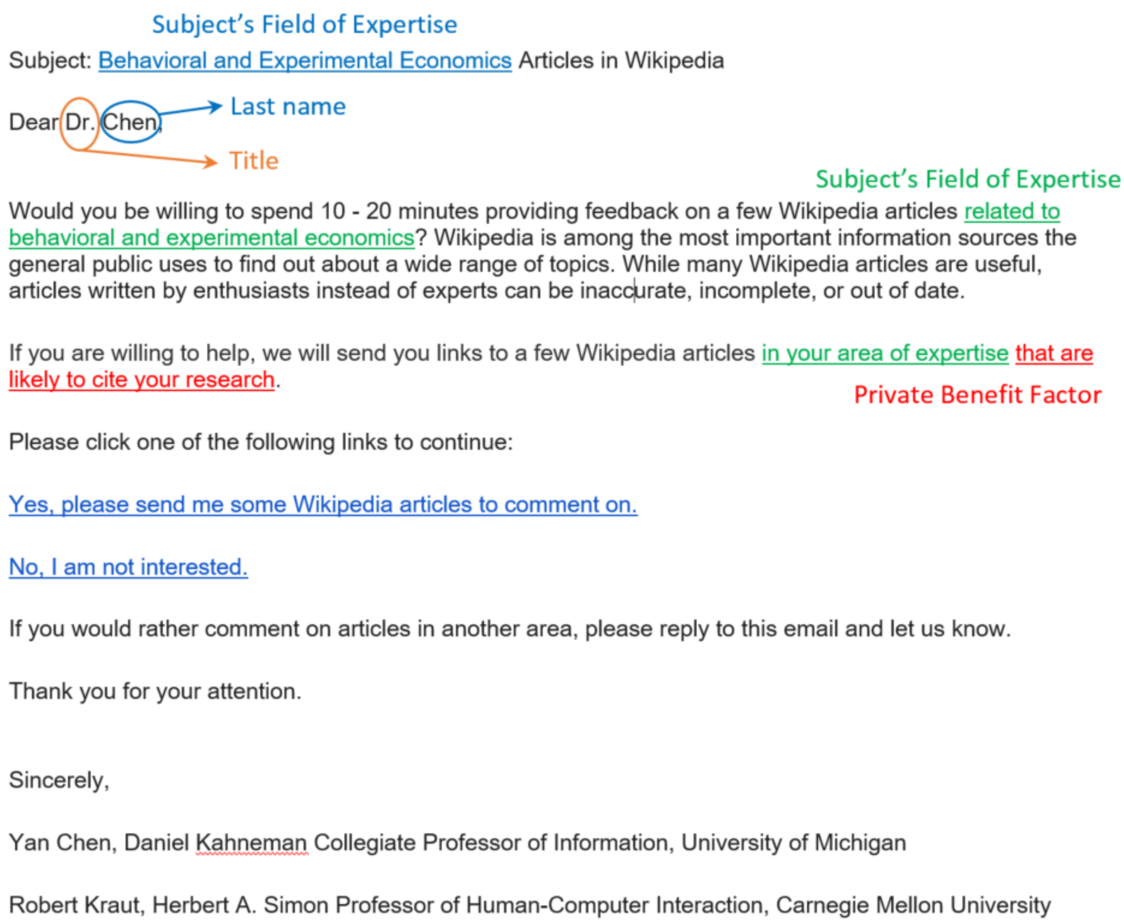
Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 6: First phase email template with only average number of views.



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If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise that are likely to cite your research.

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

If you would rather comment on articles in another area, please reply to this email and let us know.

Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 7: First phase email template with average number of views and citation benefit.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Would you be willing to spend 10 - 20 minutes providing feedback on a few Wikipedia articles related to behavioral and experimental economics? Wikipedia is among the most important information sources the general public uses to find out about a wide range of topics. While many Wikipedia articles are useful, articles written by enthusiasts instead of experts can be inaccurate, incomplete, or out of date.

If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise that are likely to cite your research. We will also acknowledge your contribution at the WikiProject Economics Page, a forum for discussion of economics articles on Wikipedia.

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 8: First phase email template with average number of views, citation, and acknowledgment benefits.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Would you be willing to spend 10 - 20 minutes providing feedback on a few Wikipedia articles related to behavioral and experimental economics? Wikipedia is among the most important information sources the general public uses to find out about a wide range of topics. While many Wikipedia articles are useful, articles written by enthusiasts instead of experts can be inaccurate, incomplete, or out of date.

If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise.

We will select only especially popular articles, with over 1,000 views in the past month, so that your feedback will benefit many Wikipedia readers.

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

If you would rather comment on articles in another area, please reply to this email and let us know.

Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 9: First phase email template with only high number of views.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen, Last name

Title

Subject's Field of Expertise

Would you be willing to spend 10 - 20 minutes providing feedback on a few Wikipedia articles related to behavioral and experimental economics? Wikipedia is among the most important information sources the general public uses to find out about a wide range of topics. While many Wikipedia articles are useful, articles written by enthusiasts instead of experts can be inaccurate, incomplete, or out of date.

Subject's Field of Expertise

If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise that are likely to cite your research.

Private Benefit Factor

We will select only especially popular articles, with over 1,000 views in the past month, so that your feedback will benefit many Wikipedia readers.

Public Benefit Factor

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 10: First phase email template with high number of views and citation benefit.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Would you be willing to spend 10 - 20 minutes providing feedback on a few Wikipedia articles related to behavioral and experimental economics? Wikipedia is among the most important information sources the general public uses to find out about a wide range of topics. While many Wikipedia articles are useful, articles written by enthusiasts instead of experts can be inaccurate, incomplete, or out of date.

If you are willing to help, we will send you links to a few Wikipedia articles in your area of expertise that are likely to cite your research. We will also acknowledge your contribution at the WikiProject Economics Page, a forum for discussion of economics articles on Wikipedia.

We will select only especially popular articles, with over 1,000 views in the past month, so that your feedback will benefit many Wikipedia readers.

Please click one of the following links to continue:

Yes, please send me some Wikipedia articles to comment on.

No, I am not interested.

Thank you for your attention.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 11: First phase email template with high number of views, citation, and acknowledgment benefits.

Subject's Field of Expertise

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Last name

Title

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics.

Subject's Field of Expertise

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness.

Wikipedia Article Title	Link to review the article
Decentralized planning (economics)	Click here
Allocative efficiency	Click here
Identity economics	Click here
Crowdsourcing	Click here
Feminist economics	Click here
School choice	Click here

We would appreciate receiving your comments by 25, May 2016. Thank you very much for your help.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 12: Second phase email template with only average number of views.

Subject's Field of Expertise

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen, Last name

Title

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics.

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness. These articles might refer to some of your research, and the comments and the references that you provide will be incorporated therein.

Private Benefit Factor

Wikipedia Article Title	Link to review the article
Decentralized planning (economics)	Click here
Allocative efficiency	Click here
Identity economics	Click here
Crowdsourcing	Click here
Feminist economics	Click here
School choice	Click here

We would appreciate receiving your comments by 25, May 2016. Thank you very much for your help.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 13: Second phase email template with average number of views and citation benefit.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen, Last name

Title

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics.

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness. These articles might refer to some of your research, and the comments and the references that you provide will be incorporated therein. We will also acknowledge your contribution at the WikiProject Economics Page, a forum for discussion of economics articles on Wikipedia.

Private Benefit Factor

Wikipedia Article Title	Link to review the article
Decentralized planning (economics)	Click here
Allocative efficiency	Click here
Identity economics	Click here
Crowdsourcing	Click here
Feminist economics	Click here
School choice	Click here

We would appreciate receiving your comments by 25, May 2016. Thank you very much for your help.

Sincerely,

Yan Chen, Daniel Kahneman Collegiate Professor of Information, University of Michigan

Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 14: Second phase email template with average number of views, citation, and acknowledgment benefits.

Subject's Field of Expertise

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Last name

Title

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics. Over the past month these suggested articles have been viewed much more frequently than the average.

Public Benefit Factor

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness.

Wikipedia Article Title	Number of views in past month	Link to review the article
Decentralized planning (economics)	114,250	Click here
Allocative efficiency	14,685	Click here
Identity economics	31,089	Click here
Crowdsourcing	281,221	Click here
Feminist economics	89,640	Click here
School choice	39,027	Click here

We would appreciate receiving your comments by 25, May 2016. Thank you very much for your help.

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Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 15: Second phase email template with only high number of views.

Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen, Last name

Title

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics. Over the past month these suggested articles have been viewed much more frequently than the average. Public Benefit Factor

Subject's Field of Expertise

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness. These articles might refer to some of your research, and the comments and the references that you provide will be incorporated therein. Private Benefit Factor

Wikipedia Article Title	Number of views in past month	Link to review the article
Decentralized planning (economics)	114,250	Click here
Allocative efficiency	14,685	Click here
Identity economics	31,089	Click here
Crowdsourcing	281,221	Click here
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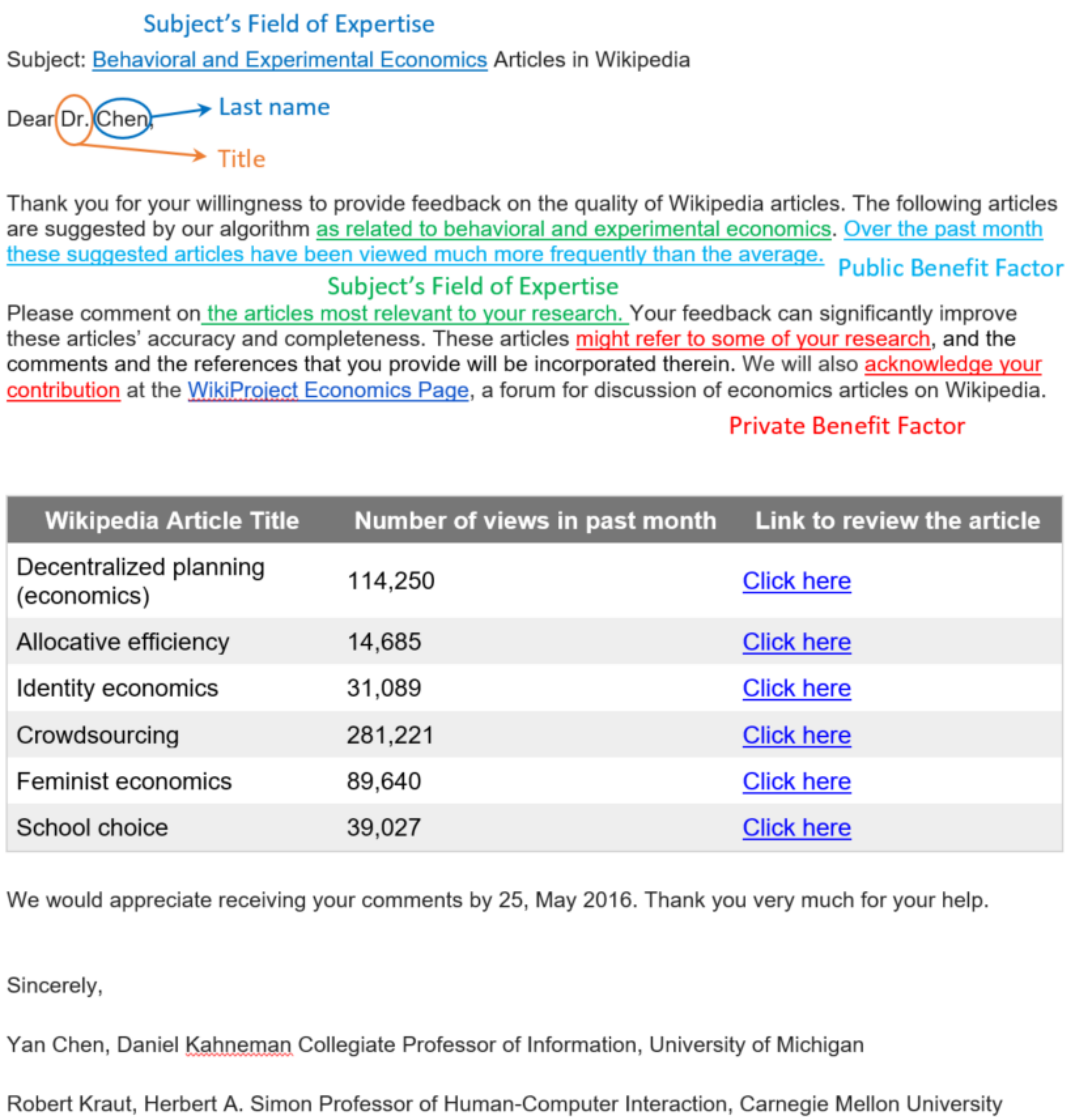
Robert Kraut, Herbert A. Simon Professor of Human-Computer Interaction, Carnegie Mellon University

Figure 16: Second phase email template with high number of views and citation benefit.



Subject: Behavioral and Experimental Economics Articles in Wikipedia

Dear Dr. Chen,

Thank you for your willingness to provide feedback on the quality of Wikipedia articles. The following articles are suggested by our algorithm as related to behavioral and experimental economics. Over the past month these suggested articles have been viewed much more frequently than the average.

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness. These articles might refer to some of your research, and the comments and the references that you provide will be incorporated therein. We will also acknowledge your contribution at the WikiProject Economics Page, a forum for discussion of economics articles on Wikipedia.

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Decentralized planning (economics)	114,250	Click here
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Figure 17: Second phase email template with high number of views, citation, and acknowledgment benefits.

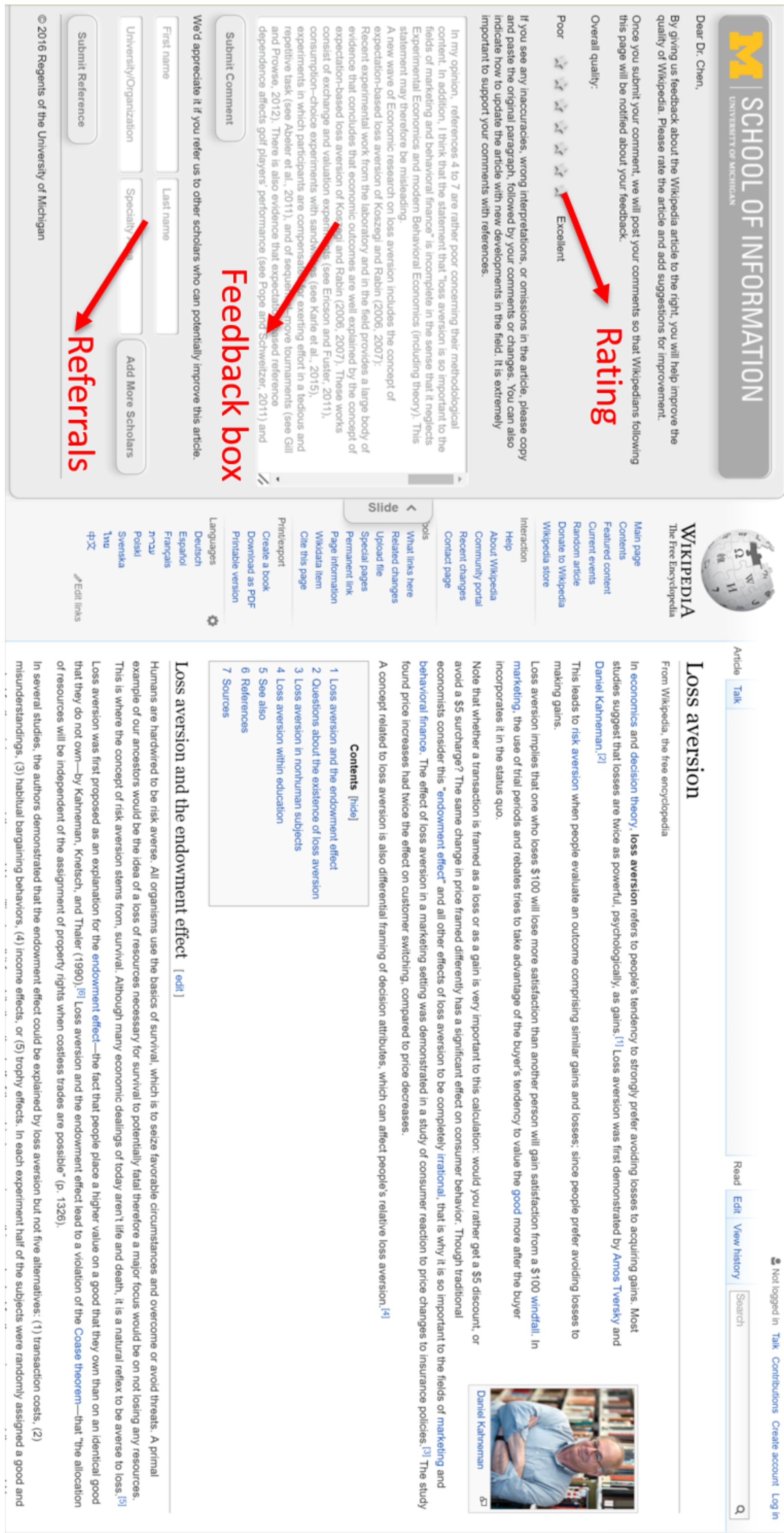

Figure 18: Commenting page

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