MANAGEMENT SCIENCE
Vol. 00, No. 0, Xxxxx 0000, pp. 000–000
ISSN 0025-1909 | EISSN 1526-5501 | 00 | 0000 | 0001

INFORMS
DOI 10.1287/xxxx.0000.0000

Electronic Companion to: Motivating Experts to Contribute to Digital Public Goods: A Personalized Field Experiment on Wikipedia

Yan Chen
School of Information, University of Michigan, Ann Arbor, MI 48109, USA, yanchen@umich.edu

Rosta Farzan
School of Computing and Information, University of Pittsburgh, 135 North Bellefield Avenue, Pittsburgh, PA 15260, USA, rfarzan@pitt.edu

Robert Kraut
School of Computer Science, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA, robert.kraut@cmu.edu

Iman YeckehZaare
School of Information, University of Michigan, Ann Arbor, MI 48109, USA, oneweb@umich.edu

Ark Fangzhou Zhang
Google, 1600 Amphitheatre Parkway, Mountain View, CA 94043, USA, arkzhang@umich.edu

Electronic Companion (EC)

The Electronic Companion (EC) contains the following sections:

EC.1. A Theoretical Framework

In this section, we outline the theoretical framework that guides our field experiment on how motivation impacts the likelihood of contributing to digital public goods. While our theoretical framework is closely related to the literature on voluntary contributions to public goods, we also incorporate features of digital public goods production into our model to better represent the context of our field experiment.

Our study centers around the question of why potential contributors choose to contribute to a public good, $y \geq 0$. To simplify notation, we use a single public good. It is straightforward to generalize the results to multiple public goods. To begin, we first let the set of potential contributors, or agents, be I, and the number of consumers of this public good be $n \geq 0$. We then specify that each agent, $i \in I$, selects a contribution level, $y_i \in [0, T_i]$, where $T_i > 0$ represents the total resources available to agent i. The quantity of the public good is obtained as the sum of all individual contributions, $y = \sum_{j \in I} y_j$.

A contributor's utility function is comprised of several components. Let the social impact of the public good be the product of the individual valuation of the public good, $f_i(y)$, and the value derived from the number of consumers, $v_i(n)$, where both $v_i(\cdot)$ and $f_i(\cdot)$ are concave. Thus, the first component of a contributor's utility function is $v_i(n)f_i(y)$, which we call the social impact of the public good. Incorporating the social impact of contributions is supported by the effects of the exogenous blocking of the Chinese Wikipedia on the contribution behavior of editors who were not blocked (**?**).

The second component is the citation benefit from the act of contribution. Previous research has shown that individuals choose to contribute to public goods due to the warm glow they receive from contributing (**??**), or the increased visibility afforded their work, which should be an increasing function of the number of consumers of the good. Our specification allows us to capture various types of citation benefits, $w_i(n)$, where $w_i(\cdot)$ is again concave. Thus, the citation benefit of contribution is captured by $w_i(n)y_i$. In the main text, we interpret citation benefit as a signal of match quality.

In comparison, a contributor's cost of contribution has two components. First, contributing $y_i \geq 0$ entails a cost in terms of the time and effort required, $c_i(y_i)$, which is assumed to be convex in y_i. Second, contributing to public goods entails an opportunity cost. Let $r_i \geq 0$ be the contributor's marginal opportunity cost. Here, we assume that contributing to the public good takes time away from other activities, such as one's own research or paid work, that would yield a citation benefit of $r_i(T_i - y_i)$. In our experiment, we measure the marginal opportunity cost, r_i, by the number of views of expert i's abstracts in a public working paper repository, which serves as a proxy for the expert's reputation.[1]

We next let $m_i \in (0,1]$ be the match quality between an expert's domain of expertise and the public good. Tasks that are matched with a potential contributor with domain expertise reduce the cost of contribution as the individual already has the required information at her disposal.[2] The quality of this match depends on the accuracy of the recommender system. Let $G(m_i)$ be the cumulative distribution function of match quality. We assume that experts share the same common prior with regard to the distribution of match quality.

After specifying the benefits and costs of individual contributions to the public good, we now model the process of contribution. To do so, we consider a two-stage process, participation and contribution, in a similar spirit as **?**.

The first stage: Participation. In the first stage, we model the expert's interest in contributing to a public good in her area of expertise. In this stage, match quality is not realized. In deciding to participate, the expert forms an expectation about the match quality and chooses to participate if the expected utility from participating dominates that of nonparticipation. Those who express interest in participating move to the second stage.

The second stage: Contribution. In the second stage, the expert observes the recommended task and, hence, the realized match quality, m_i. She then decides how much to contribute to the public good. The accuracy with which the recommended work matches her expertise, m_i, reduces the contribution cost, $c_i(y_i)/m_i$. Therefore, the more accurate the match is, the lower the contribution cost will be. Specifically, expert i solves the following optimization problem:

$$\max_{y_i \in [0,T_i]} v_i(n)f_i(y) + w_i(n)y_i + r_i(T_i - y_i) - \frac{c_i(y_i)}{m_i}. \tag{EC.1}$$

Using backward induction, we solve expert i's optimal contribution level in the second stage, y_i^*, and then solve the participation decision in the first stage. The respective proofs are relegated to Appendix EC.1. Note that the classical outcome-based utility function (EC.1) is the simplest framework that enables us to derive several relevant comparative statics results. Alternatively, one can incorporate focus weights on the citation benefit and social impact, respectively, and derive a nonlinear effect of the citation benefit on optimal contributions (**?**).

Solving the optimization problem (EC.1), we first obtain the following comparative statics for the contribution stage.

[1] In Section **??**, we show that an expert's abstract views are highly correlated with other reputation measures, such as whether the expert is ranked among the top 10% of all experts registered in the public repository.

[2] Matching an expert to tasks in her domain of expertise might also invoke her professional identity, which could also increase the value she places on the public good. For simplicity, we focus on the former and omit the latter.

Proposition EC.1 **(Contribution)**. *After an expert agrees to participate, she will contribute more if*

(a) more people consume the public good, $\frac{\partial y_i^*}{\partial n} \geq 0$*; or*

(b) the citation benefit of contribution is more salient, $\frac{\partial y_i^*}{\partial w_i} \geq 0$*; or*

(c) the match quality between the public good and her expertise is higher, $\frac{\partial y_i^*}{\partial m_i} \geq 0$*; or*

(d) her opportunity cost of time is lower, $\frac{\partial y_i^*}{\partial r_i} \leq 0$*.*

Proof: In the second stage, upon observing the realized match quality, m_i, expert i solves the following optimization problem:

$$\max_{y_i \in [0,T_i]} v_i(n) f_i\left(\sum y_{-i} + y_i\right) + w_i(n) y_i + r_i(T_i - y_i) - \frac{c_i(y_i)}{m_i}. \tag{EC.2}$$

Let y_i^* be expert i's optimal contribution level. The first order condition requires:

$$v_i(n) f_i'\left(\sum y_{-i} + y_i^*\right) + w_i(n) - r_i - \frac{c_i'(y_i^*)}{m_i} = 0. \tag{EC.3}$$

Because the valuation function for the public good, $f_i(y)$, is concave and the cost function, $c_i(y_i)$, is convex, the second order condition is satisfied:

$$v_i(n) f_i''\left(\sum y_{-i} + y_i^*\right) - \frac{c_i''(y_i^*)}{m_i} \leq 0. \tag{EC.4}$$

In what follows, we proceed to show that y_i^* is increasing in n, w_i, m_i and decreasing in r_i.

(a) An increase in the number of consumers of the public good leads to an increased level of contribution. Taking the derivative of Equation (EC.3) with respect to n, we obtain:

$$\left[v_i(n) f_i''\left(\sum y_{-i} + y_i^*\right) - \frac{c_i''(y_i^*)}{m_i}\right] \frac{\partial y_i^*}{\partial n} = -v_i'(n) f_i'\left(\sum y_{-i} + y_i^*\right) - w_i'(n).$$

Because $w_i'(n) \geq 0$, $v_i'(n) \geq 0$, $f_i'(y) \geq 0$ and (EC.4), we have:

$$\frac{\partial y_i^*}{\partial n} \geq 0.$$

(b) An increase in the citation benefit of contributions leads to an increased level of contributions. Taking the derivative of Equation (EC.3) with respect to w_i, we obtain:

$$\left[v_i(n) f_i''\left(\sum y_{-i} + y_i^*\right) - \frac{c_i''(y_i^*)}{m_i}\right] \frac{\partial y_i^*}{\partial w_i} = -1.$$

Because of the second-order condition (EC.4), we have:

$$\frac{\partial y_i^*}{\partial w_i} \geq 0.$$

(c) Better matching between the content of the public good and the agent's expertise leads to an increased level of contributions. Taking the derivative of Equation (EC.3) with respect to m_i, we obtain:

$$\left[v_i(n)f_i''\left(\sum y_{-i}+y_i^*\right)-\frac{c_i''(y_i^*)}{m_i}\right]\frac{\partial y_i^*}{\partial m_i}=-\frac{c_i'(y_i^*)}{m_i^2}.$$

Because $c_i'(y_i^*)\geq 0$ and (EC.4), we have:

$$\frac{\partial y_i^*}{\partial m_i}\geq 0.$$

(d) An expert with a higher reputation will contribute less. Taking the derivative of Equation (EC.3) with respect to r_i, we obtain:

$$\left[v_i(n)f_i''\left(\sum y_{-i}+y_i^*\right)-\frac{c_i''(y_i^*)}{m_i}\right]\frac{\partial y_i^*}{\partial r_i}=1.$$

Because of the second order condition (EC.4), we have

$$\frac{\partial y_i^*}{\partial r_i}\leq 0.$$

Q.E.D.

Going back to the first stage when the expert does not know the matching quality, we define expert i's utility difference between participating and not participating as ΔEU_i. We next solve the participation problem and obtain the following comparative statics.

PROPOSITION EC.2 **(Participation)**. *Ceteris paribus, an expert is more likely to participate if*

(a) more people consume the public good, $\frac{\partial \Delta EU_i}{\partial n}\geq 0$*; or*

(b) the citation benefit of contribution is more salient, $\frac{\partial \Delta EU_i}{\partial w_i}\geq 0$*; or*

(c) her opportunity cost of time is lower, $\frac{\partial \Delta EU_i}{\partial r_i}\leq 0$*.*

Proof: In the first stage, an expert does not see the realization of the match accuracy, m_i, but knows its distribution $G(m_i)$. Therefore, she forms her expectations for the match quality m_i.

Let $V_i(n,w_i,r_i,m_i)$ be the value function for the optimization problem in (EC.2) at optimal solution y_i^*:

$$V_i(n,w_i,r_i,m_i)=v_i(n)f_i\left(\sum y_{-i}+y_i^*\right)+w_i(n)y_i^*+r_i(T_i-y_i^*)-\frac{c_i(y_i^*)}{m_i}.$$

By the envelope theorem, we have

$$\frac{\partial V_i}{\partial n} = v_i'(n) f_i'\Big(\sum y_{-i} + y_i^*\Big) + w_i'(n) y_i^* \geq 0$$
$$\frac{\partial V_i}{\partial w_i} = y_i^* \geq 0$$
$$\frac{\partial V_i}{\partial r_i} = T_i - y_i^* \geq 0$$
$$\frac{\partial V_i}{\partial m_i} = \frac{c_i(y_i^*)}{m_i^2} \geq 0$$

In the first stage, expert i does not observe the realization of matching quality, but knows its distribution $G(m_i)$, which is assumed to have a continuous density function. If expert i chooses to participate, her expected utility is

$$EU_i(n, w_i, r_i) = \int_0^1 V_i(n, w_i, r_i, m) \mathrm{d}G(m_i). \tag{EC.5}$$

Otherwise, her utility is $U_i^0 = v_i(n) f_i\Big(\sum y_{-i}\Big) + r_i \cdot T_i$. Let the utility difference between participating and not participating be $\Delta EU_i = EU_i(n, w_i, r_i) - U_i^0$. Then an expert participates if $\Delta EU_i \geq 0$.

To prove the comparative statics in Proposition EC.2, we want to show that $\Delta EU_i(n, w_i, r_i)$ is increasing in n, w_i and decreasing r_i.

- Differentiating ΔEU_i with respect to n, we obtain:

$$\begin{aligned}
\frac{\partial \Delta EU_i}{\partial n} &= \frac{\partial}{\partial n} \int_0^1 V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) - \frac{\partial U_i^0}{\partial n} \\
&= \int_0^1 \frac{\partial}{\partial n} V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) - v_i'(n) f_i\Big(\sum y_{-i}\Big) \\
&= \int_0^1 \Big[v_i'(n) f_i'\Big(\sum y_{-i} + y_i^*\Big) + w_i'(n) y_i^* - v_i'(n) f_i\Big(\sum y_{-i}\Big)\Big] \mathrm{d}G(m_i) \\
&\geq 0.
\end{aligned}$$

- Differentiating ΔEU_i with respect to w_i, we obtain:

$$\begin{aligned}
\frac{\partial \Delta EU_i}{\partial w_i} &= \frac{\partial}{\partial w_i} \int_0^1 V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) - \frac{\partial U_i^0}{\partial w} \\
&= \int_0^1 \frac{\partial}{\partial w_i} V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) \\
&\geq 0.
\end{aligned}$$

- Differentiating ΔEU_i with respect to r_i, we obtain:

$$\begin{aligned}
\frac{\partial \Delta EU_i}{\partial r_i} &= \frac{\partial}{\partial r_i} \int_0^1 V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) - \frac{\partial U_i^0}{\partial r_i} \\
&= \int_0^1 \frac{\partial}{\partial r_i} V_i(n, w_i, r_i, m) \mathrm{d}G(m_i) - T_i \\
&= \int_0^1 [T_i - y_i^* - T_i] \mathrm{d}G(m_i) \leq 0.
\end{aligned}$$

Q.E.D.

EC.2. Recommendation algorithms

In this appendix, we describe methods used to identify experts' domains of expertise as well as those used to identify the most relevant Wikipedia articles for each expert.

We first describe the method we use to identify our experts' respective domains of expertise. To do so, we develop a filtering algorithm which is based on the experts' recent research papers archived in *New Economics Papers* (*NEP*). *NEP* is an announcement service that disseminates and archives new research papers in 97 research areas.[3] For each expert, we refer to *NEP* to obtain her recent research papers as well as the research fields where each work is classified. Then, we select the research field in which her research papers are classified most often and use that one as the most recent domain of expertise. The pseudo-code for the filtering algorithm that identifies an expert's most recent domain of expertise is presented as Algorithm 1 below.

Algorithm 1: The algorithm for identifying an expert's most recent domain of expertise.

```
foreach expert do
    ResearchList ← expert's research papers at NEP.
    foreach research paper do
        Retrieve the list of NEP categories the research paper belongs to.
        foreach category do
            specDict[category] += 1
            if specDict[category] == 7 then
                Result: Return the list of the expert's research papers under this category as
                        his or her recent research papers and the category as his or her
                        recent field of interest.
            end
        end
    end
    Data: maxSpec := the specialization in specDict with maximum # of publications.
    Result: Return the list of the expert's research papers under this category as his or her
            recent research papers and the category as his or her recent field of interest.
end
```

In what follows, we present the details for our selection criteria for Wikipedia articles. For each of an expert's research papers listed in *NEP*, the recommendation algorithm submits a search query containing the word "econ" plus the first keyword in the paper through Google Custom Search API[4]. The search result returned from Google contains Wikipedia articles that are potentially relevant for recommendation. We further restrict this list using the following criteria:

[3] See `http://nep.repec.org/`, accessed on April 27, 2022.

[4] `https://developers.google.com/custom-search/v1/overview`, accessed on April 27, 2022

1. The article must be under the namespace 0 (i.e., main articles)[5];
2. The article is not edit protected[6];
3. The length of the article is not less than 1,500 characters;
4. The article is viewed at least 1,000 times in the past 30 days (dynamically updated) prior to exposure to the intervention[7].

This way, for each publication, we obtain a list of relevant Wikipedia articles. Some of these articles are added in multiple lists of recommended articles corresponding to the publications. For up to six recent publications by the expert, we choose a Wikipedia article that appears most frequently in the result lists, for recommendation. Finally, for each of the author's publications, we identify the most relevant Wikipedia article. The pseudo-code for the algorithm that identifies the most relevant articles for each expert's recent publication is presented as Algorithm 2.

Our code for both algorithms is accessible on GitHub through the following URL: `https://github.com/ImanYZ/ExpertIdeas`, accessed on April 27, 2022. The back-end uses Python (Django framework) and MySQL Database, whereas the front-end uses HTML, CSS3 and JavaScript (JQuery).

[5] Wikipedia uses namespace to categorize webpages according to their functions. All encyclopedia articles on Wikipedia are under namespace 0. Webpages under other namespaces include talk pages and user pages. See `https://en.wikipedia.org/wiki/Wikipedia:Namespace`, accessed on April 27, 2022 for a detailed explanation of namespace at Wikipedia.

[6] The edit protection restricts a Wikipedia article from being edited by users. It is usually applied to articles that are subject to content disputes or the risk of vandalism. The decision to apply or remove edit protection is made by administrators at Wikipedia. See `https://en.wikipedia.org/wiki/Wikipedia:Protection_policy`, accessed on April 27, 2022 for a detailed explanation.

[7] This restriction guarantees that articles recommended in the AvgView condition are similar to those recommended in the HighView condition in terms of the number of views.

Algorithm 2: Algorithm for matching and recommending Wikipedia articles with an expert's most recent publications.

```
foreach expert 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) ∧
                  recommendation is not edit protected∧ recommendation is not a "Stub" ∧
                  the character length of recommendation is not less than 1,500 characters∧
                  recommendation has not been viewed less than 1,000 times over the past 30
                  days 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
```

EC.3. Screen shots

In this section, we provide screen shots of the interface design for our field experiments, starting with examples of the three emails we sent to the experts.

Our first email implements the treatments. Below is an example in the HighView & Citation treatment. Note that the order of the HighView and the Citation paragraphs was randomized for each expert before the email was sent out. In all three examples, we replace the expert's real last name by the first author's last name.

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. A Wikipedia article is viewed on average 426 times each month. 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 articles, with over 1,000 views in the past month, so that your feedback will benefit many Wikipedia readers.

These articles may include some of your publications in their references.

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 EC.1 First-stage email: An example in the HighView & Citation treatment.

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 law & economics.

Please comment on the articles most relevant to your research. Your feedback can significantly improve these articles' accuracy and completeness, and the comments and the references that you provide will be incorporated therein. These articles might refer to some of your research. We would appreciate receiving your comments by Jan 14, 2017. Thank you very much for your help.

Wikipedia Article Title	Number of views in the past month	Link to review the article
Shareholder value	6,298	Click here
Corporate governance	38,351	Click here
Managerial economics	17,771	Click here
Economic nationalism	8,931	Click here
University of Delaware	17,123	Click here
Corporatocracy	10,479	Click here

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 EC.2 Second-stage email: An example in the HighView & Citation treatment

Dear Dr. Chen,

Thank you for providing feedback on Wikipedia articles. We have posted your comments to the following article talk page(s), which is where Wikipedia editors discuss changes to articles. You can see the original article or your comments, by clicking on the appropriate links below.

Wikipedia Article	Your Comment
Shareholder value	Your comment on the Talk Page
Corporate governance	Your comment on the Talk Page
Managerial economics	Your comment on the Talk Page
Economic nationalism	Your comment on the Talk Page

Thank you again for your contribution to Wikipedia!

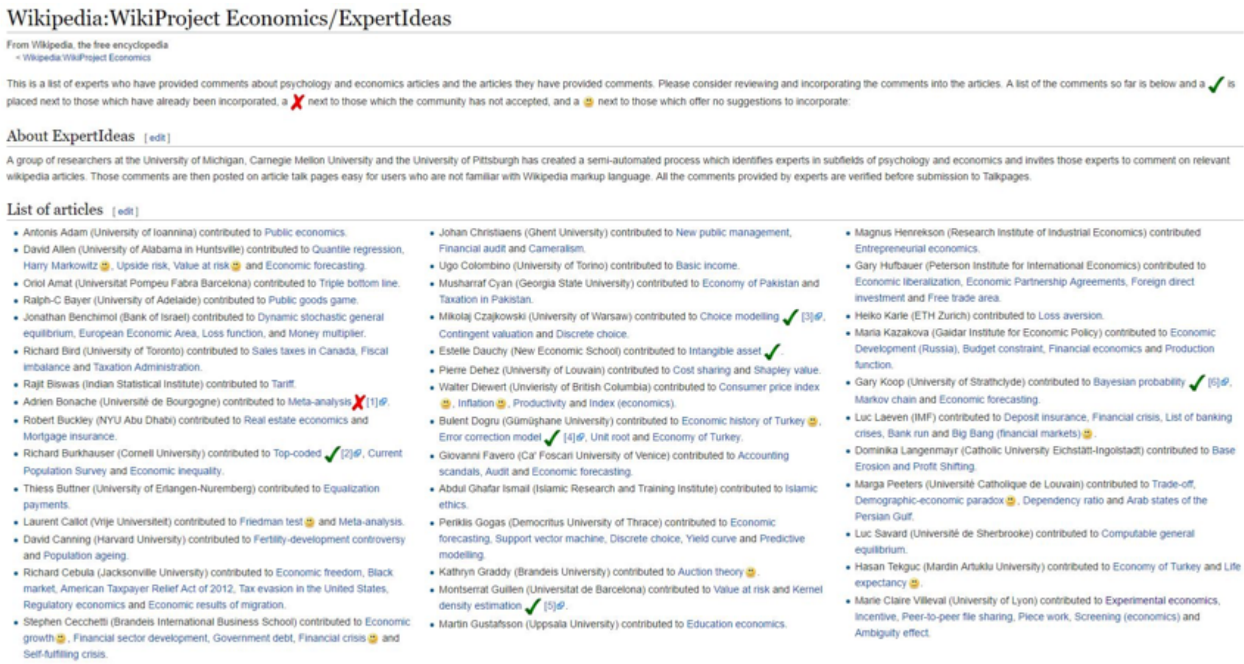
Sincerely,

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 EC.3 Thank-you Email

Figure EC.4 presents our public acknowledgement of expert contributions to Wikipedia articles. This page was assembled by a Wikipedian, Shane Murphy, who was a doctoral student in Economics at the University of Lancaster. The economists on this list contributed to our project during its pilot phase. The list was kept constant during our experiment.



Wikipedia:WikiProject Economics/ExpertIdeas

From Wikipedia, the free encyclopedia
< Wikipedia:WikiProject Economics

This is a list of experts who have provided comments about psychology and economics articles and the articles they have provided comments. Please consider reviewing and incorporating the comments into the articles. A list of the comments so far is below and a ✓ is placed next to those which have already been incorporated, a ✗ next to those which the community has not accepted, and a next to those which offer no suggestions to incorporate:

About ExpertIdeas [edit]

A group of researchers at the University of Michigan, Carnegie Mellon University and the University of Pittsburgh has created a semi-automated process which identifies experts in subfields of psychology and economics and invites those experts to comment on relevant wikipedia articles. Those comments are then posted on article talk pages easy for users who are not familiar with Wikipedia markup language. All the comments provided by experts are verified before submission to Talkpages.

List of articles [edit]

- Antonis Adam (University of Ioannina) contributed to Public economics.
- David Allen (University of Alabama in Huntsville) contributed to Quantile regression, Harry Markowitz, Upside risk, Value at risk and Economic forecasting.
- Oriol Amat (Universitat Pompeu Fabra Barcelona) contributed to Triple bottom line.
- Ralph-C Bayer (University of Adelaide) contributed to Public goods game.
- Jonathan Benchimol (Bank of Israel) contributed to Dynamic stochastic general equilibrium, European Economic Area, Loss function, and Money multiplier.
- Richard Bird (University of Toronto) contributed to Sales taxes in Canada, Fiscal imbalance and Taxation Administration.
- Rajit Biswas (Indian Statistical Institute) contributed to Tariff.
- Adrien Bonache (Université de Bourgogne) contributed to Meta-analysis ✗ [1].
- Robert Buckley (NYU Abu Dhabi) contributed to Real estate economics and Mortgage insurance.
- Richard Burkhauser (Cornell University) contributed to Top-coded ✓ [2], Current Population Survey and Economic inequality.
- Thiess Buttner (University of Erlangen-Nuremberg) contributed to Equalization payments.
- Laurent Callot (Vrije Universiteit) contributed to Friedman test and Meta-analysis.
- David Canning (Harvard University) contributed to Fertility-development controversy and Population ageing.
- Richard Cebula (Jacksonville University) contributed to Economic freedom, Black market, American Taxpayer Relief Act of 2012, Tax evasion in the United States, Regulatory economics and Economic results of migration.
- Stephen Cecchetti (Brandeis International Business School) contributed to Economic growth, Financial sector development, Government debt, Financial crisis and Self-fulfilling crisis.
- Johan Christiaens (Ghent University) contributed to New public management, Financial audit and Cameralism.
- Ugo Colombino (University of Torino) contributed to Basic income.
- Musharraf Cyan (Georgia State University) contributed to Economy of Pakistan and Taxation in Pakistan.
- Mikolaj Czajkowski (University of Warsaw) contributed to Choice modelling ✓ [3], Contingent valuation and Discrete choice.
- Estelle Dauchy (New Economic School) contributed to Intangible asset ✓.
- Pierre Dehez (University of Louvain) contributed to Cost sharing and Shapley value.
- Walter Diewert (Unvieristy of British Columbia) contributed to Consumer price index, Inflation, Productivity and Index (economics).
- Bulent Dogru (Gümüşhane University) contributed to Economic history of Turkey, Error correction model ✓ [4], Unit root and Economy of Turkey.
- Giovanni Favero (Ca' Foscari University of Venice) contributed to Accounting scandals, Audit and Economic forecasting.
- Abdul Ghafar Ismail (Islamic Research and Training Institute) contributed to Islamic ethics.
- Periklis Gogas (Democritus University of Thrace) contributed to Economic forecasting, Support vector machine, Discrete choice, Yield curve and Predictive modelling.
- Kathryn Graddy (Brandeis University) contributed to Auction theory.
- Montserrat Guillen (Universitat de Barcelona) contributed to Value at risk and Kernel density estimation ✓ [5].
- Martin Gustafsson (Uppsala University) contributed to Education economics.
- Magnus Henrekson (Research Institute of Industrial Economics) contributed Entrepreneurial economics.
- Gary Hufbauer (Peterson Institute for International Economics) contributed to Economic liberalization, Economic Partnership Agreements, Foreign direct investment and Free trade area.
- Heiko Karle (ETH Zurich) contributed to Loss aversion.
- Maria Kazakova (Gaidar Institute for Economic Policy) contributed to Economic Development (Russia), Budget constraint, Financial economics and Production function.
- Gary Koop (University of Strathclyde) contributed to Bayesian probability ✓ [6], Markov chain and Economic forecasting.
- Luc Laeven (IMF) contributed to Deposit insurance, Financial crisis, List of banking crises, Bank run and Big Bang (financial markets).
- Dominika Langenmayr (Catholic University Eichstätt-Ingolstadt) contributed to Base Erosion and Profit Shifting.
- Marga Peeters (Université Catholique de Louvain) contributed to Trade-off, Demographic-economic paradox, Dependency ratio and Arab states of the Persian Gulf.
- Luc Savard (Université de Sherbrooke) contributed to Computable general equilibrium.
- Hasan Tekguc (Mardin Artuklu University) contributed to Economy of Turkey and Life expectancy.
- Marie Claire Villeval (University of Lyon) contributed to Experimental economics, Incentive, Peer-to-peer file sharing, Piece work, Screening (economics) and Ambiguity effect.

Figure EC.4 Public Acknowledgement Hosted on a WikiProject Economics Page

A larger version of this page hosted on Wikipedia can be accessed through the following URL: `https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Economics/ExpertIdeas`, accessed on April 27, 2022.

Figure EC.5 presents our webpage where experts enter their comments. The interface is designed to minimize entry cost. An expert does not need to know how to edit a wiki. In the split screen design, the right side is the corresponding Wikipedia article that the expert can scroll up or down. The left side has a quality rating and a text box for the expert to enter comments. Thus, the process only requires knowledge of Word.

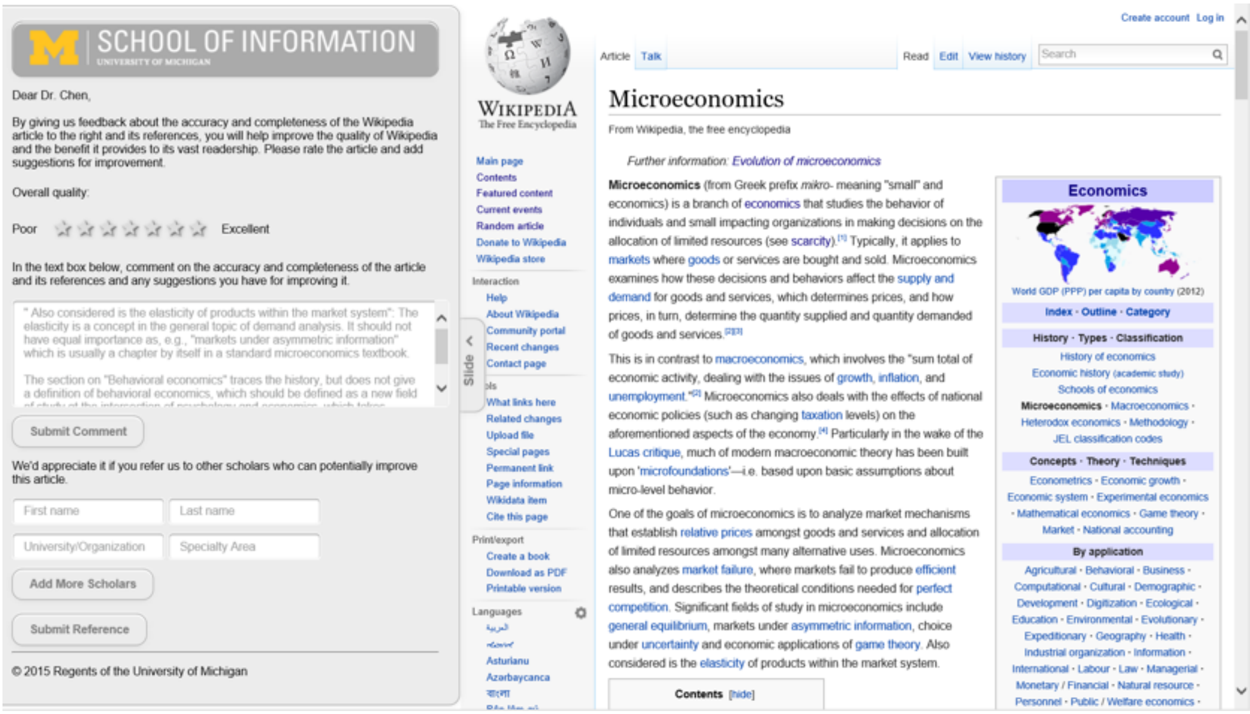


Figure EC.5 Web interface for experts to enter comments

EC.4. Additional Analyses and Robustness Checks

EC.4.1. First-stage Response

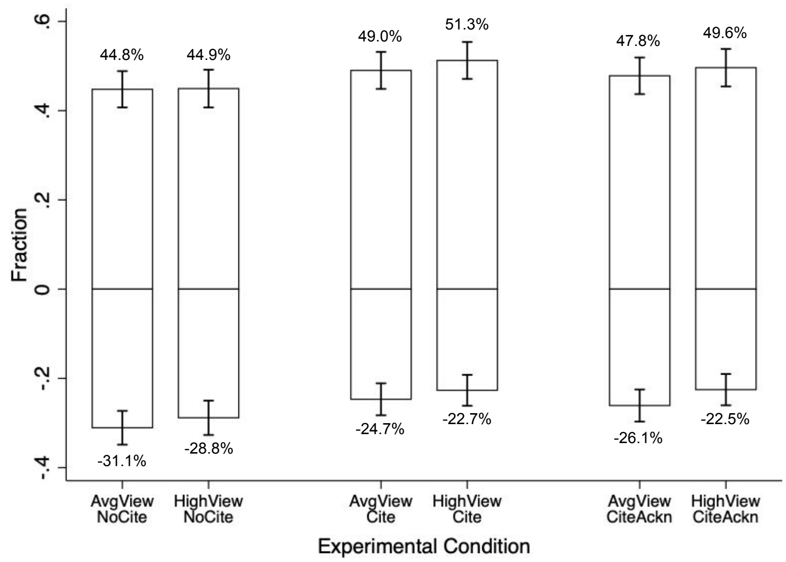


Figure EC.6 Fraction of positive and negative responses among the treated experts in the first stage: Error bars denote one standard error of the mean (Sample size: 3,346).

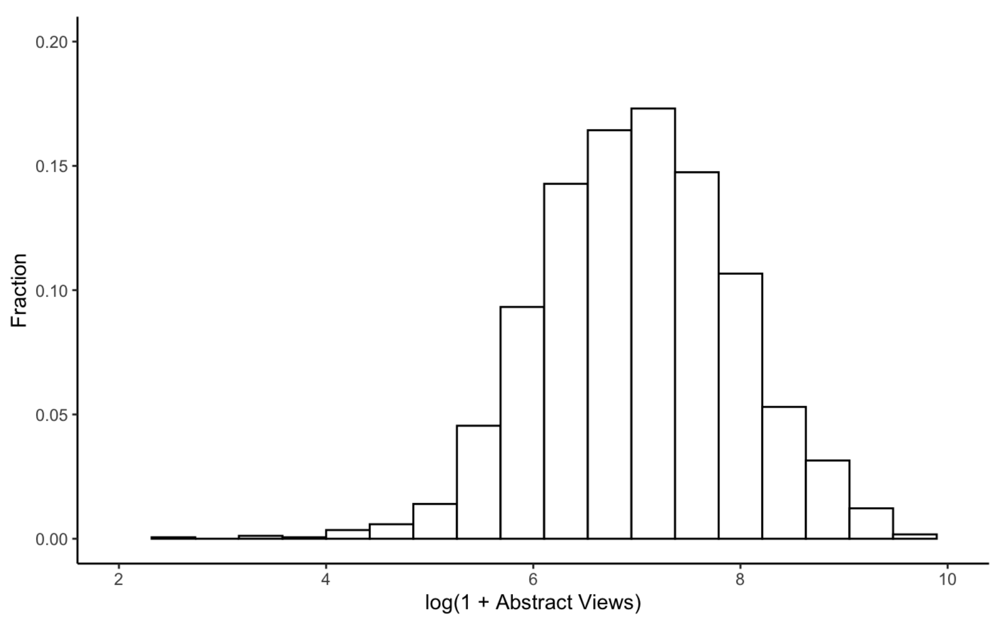


Figure EC.7 Empirical distribution of author abstract views for experts in our sample (Sample size: 3,346)

Table EC.1 reports the results for the average marginal effects estimated from the multinomial logistic specifications. Under the high view condition, estimates for the average marginal effect is 6.3 p.p. for Cite + HighView × Cite ($p < 0.05$, $q = 0.119$), corresponding to a 13% increase over the baseline response rate of 45%. In comparison, under the average view condition, the likelihood of a negative response is reduced by 6.6 p.p. with citation benefits ($p < 0.05$, $q = 0.038$). The results remain robust using percentile measures of abstract views (Table EC.2).

Columns (4) through (6) provide the results for the average marginal effects from the multinomial logistic regression including expert-level controls. Note that the empirical distribution of Abstract Views is skewed toward zero (see Figure EC.7). To mitigate any potential effect of extreme values, we apply both a logarithmic transformation (Table EC.1) and percentile ranking (Table EC.2) to Abstract Views in the regression. Doing so, we find that the effect of log(1 + Abstract Views) on negative response is 3 p.p. ($p < 0.01$). From a back-of-the-envelope calculation, we find that a one standard deviation increase in log(1 + Abstract Views) is associated with a 25 p.p. increase in the likelihood of a negative response. Similarly, we find that experts affiliated with an institution from an English-speaking country are 5.7 p.p. more likely to decline the invitation ($p < 0.01$).

Table EC.1 Average Marginal Effect on the First-stage Response: Multinomial Logit with Log Abstract Views

	Positive Response (1)	No Response (2)	Negative Response (3)	Positive Response (4)	No Response (5)	Negative Response (6)
HighView	0.002	0.021	-0.022	0.004	0.019	-0.023
	(0.030)	(0.026)	(0.027)	(0.030)	(0.026)	(0.027)
	[1.000]	[0.989]	[0.977]	[1.000]	[0.987]	[0.972]
Cite	0.042	0.022	-0.064**	0.037	0.029	-0.066**
	(0.030)	(0.026)	(0.027)	(0.030)	(0.026)	(0.026)
	[0.690]	[0.972]	[0.107]	[0.808]	[0.877]	[0.081]
CiteAckn	0.030	0.020	-0.050*	0.020	0.025	-0.045*
	(0.029)	(0.026)	(0.027)	(0.030)	(0.026)	(0.027)
	[0.922]	[0.983]	[0.356]	[0.993]	[0.940]	[0.503]
HighView × Cite	0.021	-0.023	0.002	0.023	-0.028	0.005
	(0.042)	(0.037)	(0.037)	(0.042)	(0.037)	(0.037)
HighView × CiteAckn	0.017	-0.003	-0.013	0.022	-0.007	-0.014
	(0.042)	(0.037)	(0.038)	(0.042)	(0.037)	(0.038)
log(1 + Abstract Views)				0.009	-0.039***	0.030***
				(0.009)	(0.008)	(0.008)
English Affiliation				-0.020	-0.037**	0.057***
				(0.018)	(0.015)	(0.015)
HighView + HighView × Cite	0.022	-0.002	-0.020	0.027	-0.009	-0.018
	(0.030)	(0.026)	(0.025)	(0.030)	(0.026)	(0.025)
	[0.986]	[1.000]	[0.980]	[0.962]	[1.000]	[0.990]
Cite + HighView × Cite	0.063**	-0.001	-0.062**	0.060**	0.001	-0.061**
	(0.030)	(0.027)	(0.026)	(0.030)	(0.026)	(0.026)
	[0.232]	[1.000]	[0.132]	[0.286]	[1.000]	[0.132]
HighView + HighView × CiteAckn	0.018	0.017	-0.036	0.025	0.012	-0.037
	(0.030)	(0.027)	(0.026)	(0.030)	(0.027)	(0.026)
	[0.996]	[0.993]	[0.715]	[0.971]	[0.999]	[0.679]
CiteAckn + HighView × CiteAckn	0.047	0.016	-0.063**	0.041	0.018	-0.059**
	(0.030)	(0.027)	(0.027)	(0.030)	(0.027)	(0.027)
	[0.598]	[0.996]	[0.113]	[0.738]	[0.994]	[0.168]
Observations		3,346			3,301	

Notes. The dependent variable is the expert's response to the email in the first stage. Standard errors are provided in parentheses, whereas q-values in square brackets adjust for multiple hypothesis testing using the Holm-Šidák correction. Average marginal effects are calculated using the Delta method (**?**). *, ** and *** denote significance at 10%, 5% and 1% level. In Specifications (4)-(6), 45 observations are dropped from the regression as the information about author abstract views or English affiliation is not available. Table EC.2 in Appendix EC.4.1 provides the results of a robustness check using percentile measures of Abstract Views.

Table EC.2 Average Marginal Effect on the First-stage Response: Multinomial Logit with Percentile of Abstract Views

Dependent Variable:	Positive P($R=1$) (1)	Null P($R=0$) (2)	Negative P($R=-1$) (3)	Positive P($R=1$) (4)	Null P($R=0$) (5)	Negative P($R=-1$) (6)
HighView	0.002	0.021	-0.022	0.004	0.018	-0.022
	(0.030)	(0.026)	(0.027)	(0.030)	(0.026)	(0.027)
	[1.000]	[0.979]	[0.977]	[1.000]	[0.990]	[0.977]
Cite	0.042	0.022	-0.064**	0.037	0.030	-0.067**
	(0.030)	(0.026)	(0.027)	(0.030)	(0.026)	(0.026)
	[0.690]	[0.972]	[0.107]	[0.813]	[0.864]	[0.075]
CiteAckn	0.030	0.020	-0.050*	0.020	0.024	-0.044*
	(0.029)	(0.026)	(0.027)	(0.030)	(0.026)	(0.027)
	[0.922]	[0.983]	[0.356]	[0.993]	[0.945]	[0.518]
HighView × Cite	0.021	-0.023	0.002	0.023	-0.028	0.005
	(0.042)	(0.037)	(0.037)	(0.042)	(0.037)	(0.037)
HighView × CiteAckn	0.017	-0.003	-0.013	0.021	-0.005	-0.016
	(0.042)	(0.037)	(0.038)	(0.042)	(0.037)	(0.038)
Percentile of Abstract Views				0.029	-0.134***	0.105***
				(0.030)	(0.026)	(0.026)
English Affiliation				-0.020	-0.037**	0.057***
				(0.018)	(0.015)	(0.015)
HighView + HighView × Cite	0.022	-0.002	-0.020	0.027	-0.010	-0.017
	(0.030)	(0.026)	(0.025)	(0.030)	(0.026)	(0.025)
	[0.986]	[1.000]	[0.372]	[0.960]	[1.000]	[0.992]
Cite + HighView × Cite	0.063**	-0.001	-0.062**	0.060**	0.002	-0.062**
	(0.030)	(0.027)	(0.026)	(0.030)	(0.026)	(0.026)
	[0.232]	[1.000]	[0.132]	[0.286]	[1.000]	[0.126]
HighView + HighView × CiteAckn	0.018	0.017	-0.036	0.025	0.013	-0.038
	(0.030)	(0.027)	(0.026)	(0.030)	(0.027)	(0.026)
	[0.996]	[0.993]	[0.715]	[0.972]	[1.000]	[0.655]
CiteAckn + HighView × CiteAckn	0.047	0.016	-0.063**	0.041	0.019	-0.060**
	(0.030)	(0.027)	(0.027)	(0.030)	(0.027)	(0.027)
	[0.598]	[0.996]	[0.113]	[0.746]	[0.990]	[0.156]
Model Specification	Multinomial Logistic			Multinomial Logistic		
Observations	3,346			3,301		

Notes. The dependent variable is the expert's response to the email in the first stage. Standard errors are provided in parentheses, whereas q-avlues in square brackets adjust for multiple hypothesis testing using the Holm-Šidák correction. Average marginal effects are calculated using the Delta Method. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

EC.4.2. Second-stage Analysis

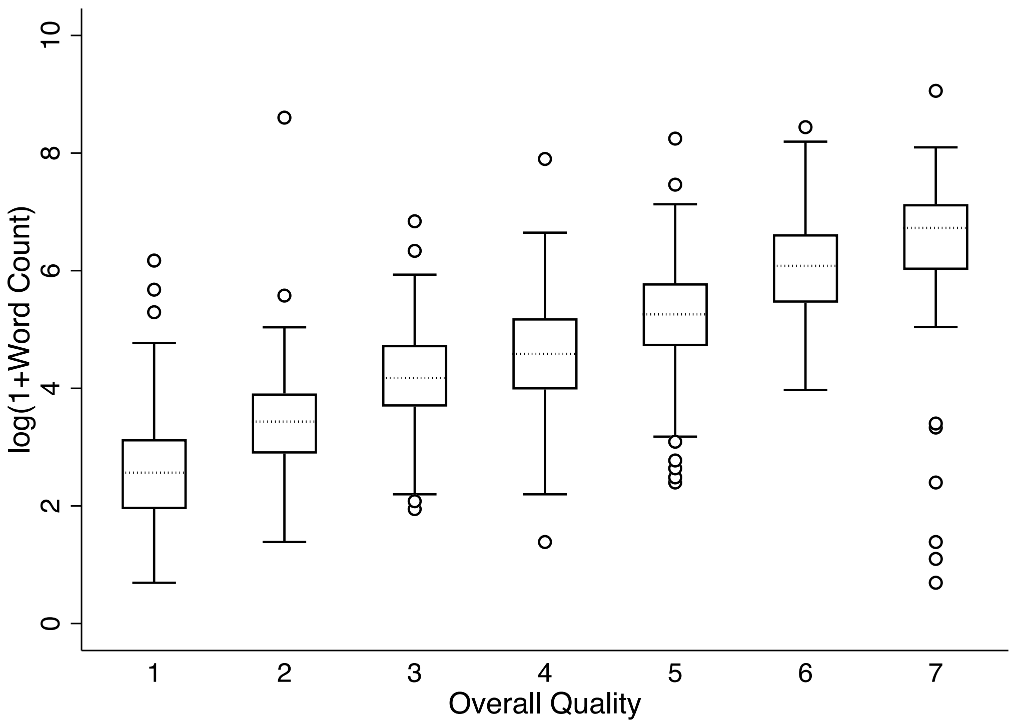


Figure EC.8 Word count and median rater's overall quality rating (Sample size: 1,188)

EC.4.2.1. Measurements: Contribution Length, Quality, and Match Quality

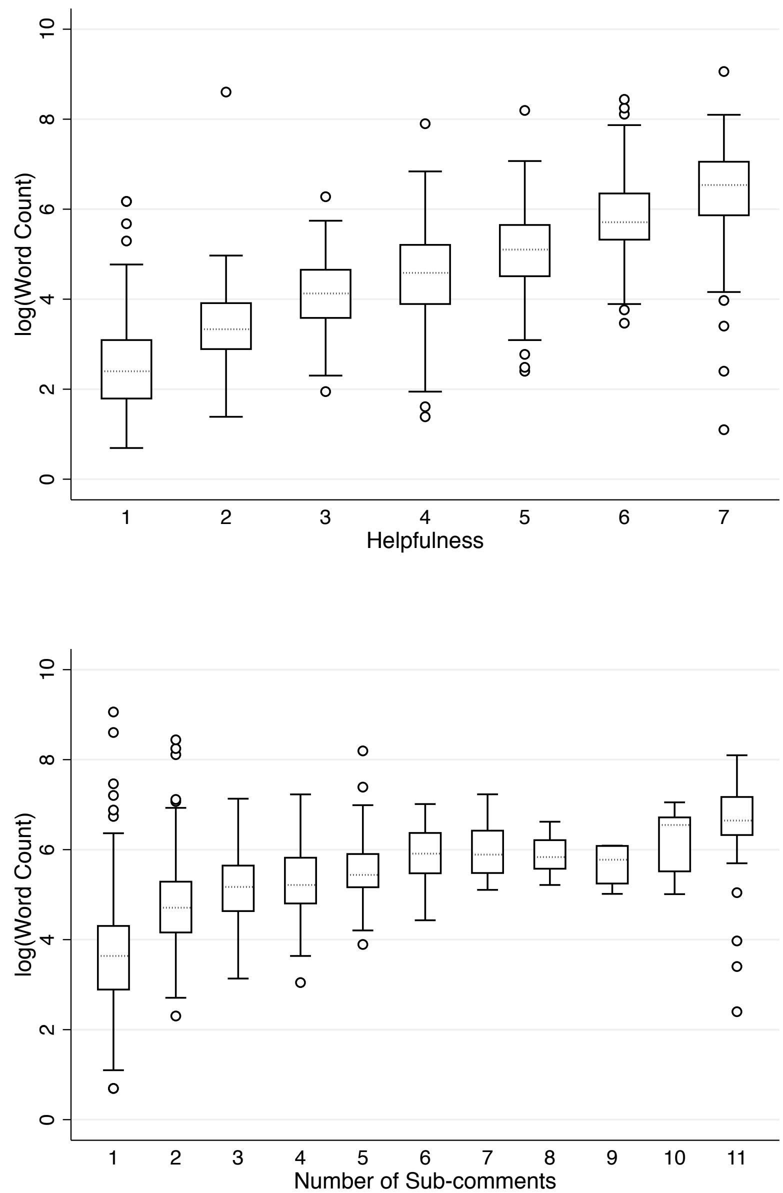


Figure EC.9 **Word count and median helpfulness (upper panel, sample size: 1,188); Word count and median number of subcomments within a comment (lower panel, sample size: 1,188)**

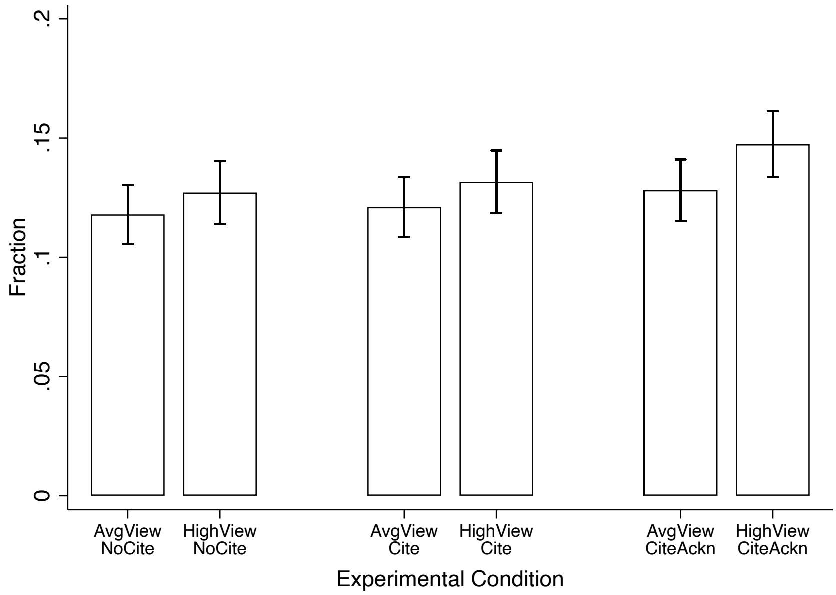


Figure EC.10 Fraction of experts contributing to any article by experimental condition: Error bars denote one standard error of the mean (Sample size: 3,346)

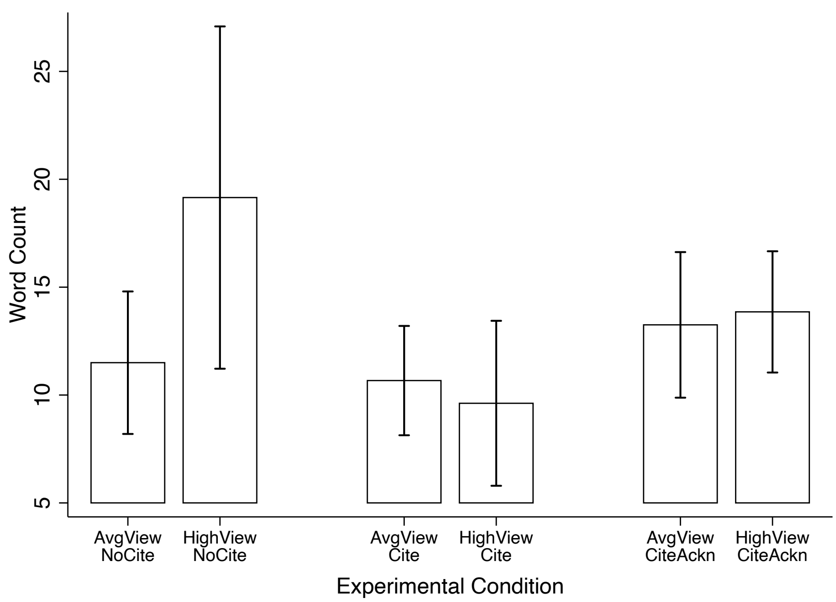


Figure EC.11 Word count by experimental conditions treating non-contribution as zeros (Sample size: 19,333)

EC.4.2.2. Unconditional Analyses of Contribution Length and Quality

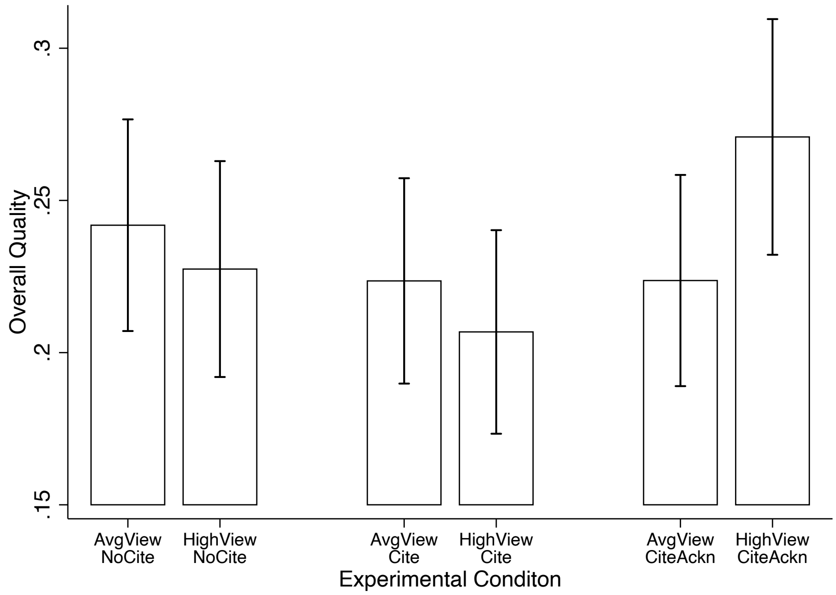


Figure EC.12 Overall quality by experimental conditions treating non-contribution as zeros (Sample size: 19,333)

Table EC.3 Average Marginal Effect on Overall Quality (Unconditional)

Dependent Variable:	Overall Quality						
	$\mathrm{P}(Y=1)$	$\mathrm{P}(Y=2)$	$\mathrm{P}(Y=3)$	$\mathrm{P}(Y=4)$	$\mathrm{P}(Y=5)$	$\mathrm{P}(Y=6)$	$\mathrm{P}(Y=7)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Specification	Ordered Logistic						
HighView	-0.003	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Cite	-0.000	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.000)
	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]
CiteAckn	-0.001	-0.001	-0.002	-0.003	-0.003	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.000)
	[0.913]	[0.910]	[0.907]	[0.908]	[0.905]	[0.905]	[0.908]
HighView × Cite	-0.001	-0.000	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)	(0.000)
HighView × CiteAckn	0.001	0.002	0.003	0.005	0.005	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)
Cosine Similarity	0.007***	0.010***	0.018***	0.028***	0.031***	0.010***	0.004***
	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.001)
log(Article Length)	-0.000**	-0.001**	-0.001**	-0.002**	-0.002**	-0.001**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
log(1 + Abstract Views)	-0.000*	0.000	0.001	0.001*	0.001*	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
English Affiliation	0.000	0.001	0.001	0.002	0.002	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
HighView + HighView × Cite	-0.000	-0.001	-0.001	-0.002	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)
	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]
Cite + HighView × Cite	-0.000	-0.001	-0.001	-0.002	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)
	[0.987]	[0.987]	[0.986]	[0.986]	[0.986]	[0.987]	[0.987]
HighView + HighView × CiteAckn	0.001	0.001	0.002	0.003	0.004	0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	0.000
	[0.740]	[0.740]	[0.733]	[0.731]	[0.724]	[0.738]	[0.738]
CiteAckn + HighView × CiteAckn	0.000	0.001	0.001	0.002	0.002	0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	0.000
	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]	[0.991]
Observations (Recommended Articles)	18,873						
Clusters (Experts)	3,301						

Notes. Columns (1)-(7) report the average marginal effects on the probability that median overall quality receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the expert level. and clustered at the level of expert. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.4 Average Marginal Effect on Helpfulness (Unconditional)

Dependent Variable:	Helpfulness						
	P($Y=1$)	P($Y=2$)	P($Y=3$)	P($Y=4$)	P($Y=5$)	P($Y=6$)	P($Y=7$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Specification	Ordered Logistic						
HighView	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.000)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Cite	-0.000	-0.000	-0.001	-0.001	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.000)
	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]
CiteAckn	-0.001	-0.001	-0.001	-0.003	-0.003	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.000)
	[0.907]	[0.908]	[0.908]	[0.903]	[0.904]	[0.904]	[0.908]
HighView × Cite	-0.000	-0.001	-0.000	-0.000	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.002)	(0.001)
HighView × CiteAckn	0.001	0.001	0.002	0.005	0.006	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.002)	(0.001)
Cosine Similarity	0.007***	0.008***	0.015***	0.028***	0.033***	0.013***	0.005***
	(0.001)	(0.002)	(0.003)	(0.005)	(0.006)	(0.002)	(0.001)
log(Article Length)	-0.000**	-0.000**	-0.001**	-0.002**	-0.002**	-0.001**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.000)
log(1 + Abstract Views)	0.000*	0.000	0.001	0.001*	0.002*	0.001*	0.000*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
English Affiliation	0.000	0.000	0.001	0.002	0.002	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
HighView + HighView × Cite	-0.000	-0.000	-0.001	-0.002	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.000)
	[0.992]	[0.993]	[0.992]	[0.992]	[0.992]	[0.992]	[0.992]
Cite + HighView × Cite	-0.000	-0.001	-0.001	-0.002	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.000)
	[0.989]	[0.989]	[0.988]	[0.988]	[0.988]	[0.988]	[0.988]
HighView + HighView × CiteAckn	0.001	0.001	0.002	0.003	0.004	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	0.000
	[0.733]	[0.731]	[0.729]	[0.724]	[0.719]	[0.719]	[0.751]
CiteAckn + HighView × CiteAckn	0.000	0.001	0.001	0.002	0.002	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.000)
	[0.990]	[0.990]	[0.990]	[0.991]	[0.990]	[0.991]	[0.991]
Observations (Recommended Articles)	18,873						
Clusters (Experts)	3,301						

Notes. Columns (1)-(7) report the average marginal effects on the probability that median overall quality receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the level of expert. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.5 Average Marginal Effect on # of Sub-comments (Unconditional)

Model Specification	Poisson
Dependent Variable:	# of Sub-comments
HighView	-0.031
	(0.034)
	[0.957]
Cite	-0.029
	(0.033)
	[0.960]
CiteAckn	-0.015
	(0.035)
	[1.000]
HighView × Cite	0.014
	(0.042)
HighView × CiteAckn	0.053
	(0.047)
Cosine Similarity	0.435***
	(0.061)
log(Article Length)	-0.006
	(0.010)
log(1 + Abstract Views)	0.012
	(0.010)
English Affiliation	0.017
	(0.018)
HighView + HighView × Cite	-0.018
	(0.025)
	[0.990]
Cite + HighView × Cite	-0.016
	(0.027)
	[0.997]
HighView + HighView × CiteAckn	0.022
	(0.032)
	[0.991]
CiteAckn + HighView × CiteAckn	0.039
	(0.032)
	[0.826]
Observations (Recommended Articles)	18,873
Clusters (Experts)	3,301

Notes. Columns (1)-(7) report the average marginal effects on the number of subcomments receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the level of expert. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.6 Determinants of Contribution Length (Unconditional): Interacting log abstract views with cosine similarity

Dependent Variable:	log(1 + Word Count) (1)	(2)
Model Specification	OLS	Exp. Disp.
HighView	-0.020	0.076
	(0.049)	(0.719)
	[1.000]	[1.000]
Cite	-0.013	0.021
	(0.049)	(0.718)
	[1.000]	[1.000]
CiteAckn	-0.028	0.021
	(0.049)	(0.714)
	[0.997]	[1.000]
HighView × Cite	-0.012	0.007
	(0.066)	(1.008)
HighView × CiteAckn	0.092	0.208
	(0.070)	(0.993)
Cosine Similarity	-0.053	1.619
	(0.641)	(2.965)
log(1 + Abstract Views)	0.010	0.014
	(0.017)	(0.233)
Cosine Similarity × log(1 + Abstract Views)	0.114	0.203
	(0.091)	(0.412)
log(Article Length)	-0.015	-0.037
	(0.011)	(0.064)
English Affiliation	0.034	0.066
	(0.029)	(0.410)
HighView + HighView × Cite	-0.032	0.084
	(0.044).	(0.708)
	[0.987]	[1.000]
Cite + HighView × Cite	-0.025	0.028
	(0.043)	(0.709)
	[0.997]	[1.000]
HighView + HighView × CiteAckn	0.072	0.285
	(0.049)	(0.685)
	[0.674]	[1.000]
CiteAckn + HighView × CiteAckn	0.064	0.229
	(0.050)	(0.690)
	[0.794]	[1.000]
Observations (Recommended Articles)	19,333	19,333
Clusters (Experts)	3,346	3,346

Notes. Quality class and importance class are controlled for in all specifications. Expert fixed effects are included. Standard errors in parentheses are clustered at the expert level, whereas q-values in square brackets adjust for multiple hypothesis testing using the Holm-Šidák correction. *, ** and *** denote significance level at 10%, 5% and 1% level. The number of recommended articles refers to the total number of Wikipedia articles to experts who responded positively in the first stage.

Table EC.7 Determinants of contribution length (unconditional): Using half abstract to compute cosine similarity

Dependent Variable:	log(1 + Word Count)					
	(1)	(2)	(3)	(4)	(5)	(6)
Model Specification	OLS	Exp. Disp.	OLS	Exp. Disp.	OLS	Exp. Disp
Cosine Similarity from Half Abstract?	/	/	No	No	Yes	Yes
HighView	-0.016	0.103	-0.021	0.075	-0.021	0.091
	(0.049)	(0.732)	(0.049)	(0.719)	(-0.047)	(0.716)
	[0.999]	[0.997]	[0.999]	[0.999]	[1.000]	[1.000]
Cite	-0.005	0.061	-0.013	0.020	-0.014	0.021
	(0.049)	(0.731)	(0.049)	(0.718)	(0.047)	(0.716)
	[0.999]	[0.987]	[0.999]	[0.999]	[1.000]	[1.000]
CiteAckn	-0.011	0.106	-0.028	0.020	-0.029	0.020
	(0.048)	(0.722)	(0.049)	(0.713)	(0.047)	(0.712)
	[0.999]	[0.946]	[0.999]	[0.997]	[0.996]	[1.000]
HighView × Cite	-0.019	-0.042	-0.012	0.008	-0.013	-0.011
	(0.065)	(1.027)	(0.066)	(1.008)	(0.067)	(1.005)
HighView × CiteAckn	0.076	0.139	0.092	0.210	0.090	0.210
	(0.069)	(1.006)	(0.070)	(0.993)	(0.067)	(0.989)
Cosine Similarity			0.750***	3.068***	0.745***	2.904***
			(0.088)	(0.377)	(0.072).	(0.356)
log(Article Length)			-0.015	-0.038	-0.009	-0.007
			(0.012)	(0.064)	(0.013)	(0.064)
log(1 + Abstract Views)			0.026*	0.047	0.025	0.043
			(0.015)	(0.224)	(0.015)	(0.224)
English Affiliation			0.035	0.066	0.034	0.060
			(0.029)	(0.410)	(0.028)	(0.408)
HighView + HighView × Cite	-0.035	0.061	-0.032	0.083	-0.034	0.080
	(0.044)	(0.719)	(0.044)	(0.708)	(0.047)	(0.706)
	[0.979]	[0.999]	[0.986]	[0.979]	[0.983]	[1.000]
Cite + HighView × Cite	-0.023	0.019	-0.025	-0.296	-0.027	0.010
	(0.043)	(0.721)	(0.043)	(0.215)	(0.048)	(0.706)
	[0.998]	[0.999]	[0.997]	[0.999]	[0.995]	[1.000]
HighView + HighView × CiteAckn	0.059	0.241	0.071	0.285	0.069	0.301
	(0.049)	(0.690)	(0.049)	(0.685)	(0.047)	(0.682)
	[0.827]	[0.799]	[0.674]	[0.799]	[0.700]	[1.000]
CiteAckn + HighView × CiteAckn	0.064	0.245	0.064	0.229	0.061	0.230
	(0.049)	(0.701)	(0.050)	(0.690)	(0.048)	(0.685)
	[0.769]	[0.799]	[0.796]	[0.867]	[0.823]	[1.000]
Observations (Recommended Articles)	19,333	19,333	18,873	18,873	18,873	18,873
Clusters (Experts)	3,346	3,346	3,301	3,301	3,301	3,301

Notes. Quality class and importance class are controlled for in all specifications. Expert fixed effects are included. Standard errors in parentheses are clustered at the expert level, whereas q-values in square brackets adjust for multiple hypothesis testing using the Holm-Šidák correction. *, ** and *** denote significance level at 10%, 5% and 1% level. The number of recommended articles refers to the total number of Wikipedia articles to experts who responded positively in the first stage.

EC.4.2.3. Prediction: The Random Forest Model The complete list of features in our random forest model is as follows:

1. Expert characteristics:
   (a) year of PhD;
   (b) gender;
   (c) specialization;[8]
   (d) author abstract views on RePEc;
   (e) among the top 10% of registered RePEc authors;
   (f) academic institution located in an English-speaking country.
2. Wikipedia article characteristics:
   (a) Article length (word count);
   (b) Article importance class:
      i. Top Importance;
      ii. High Importance;
      iii. Mid Importance;
      iv. Low Importance.
   (c) Article quality class:[9]
      i. Featured Article;
      ii. Good Article;
      iii. B;
      iv. C.
3. Match quality between an expert's paper abstract and their assigned Wikipedia article:
   (a) cosine similarity.
4. Treatment status:
   (a) Cite;
   (b) Cite-Acknowledgement;
   (c) High View.

Figure EC.13 presents a simplified version of a decision tree using only two features, author abstract view and cosine similarity. The tree splits in two at every node. At each node, the value of

[8] We first retrieve the experts' specializations according to the JEL classification from RePEc, with a total of 69 different values. To reduce the dimensionality of the feature space, we further group them into 8 categories, including: 1) Mathematical and microeconomics, 2) Macroeconomics and monetary economics, 3) International economics, 4) Finance, 5) Public, health and labor economics, 6) Industrial organization and regulatory economics, 7) Economic history, 8)ZQ Development economics.

[9] We exclude Start and Stub quality classes from our model as articles from these two classes account for less than 1% of our sample.

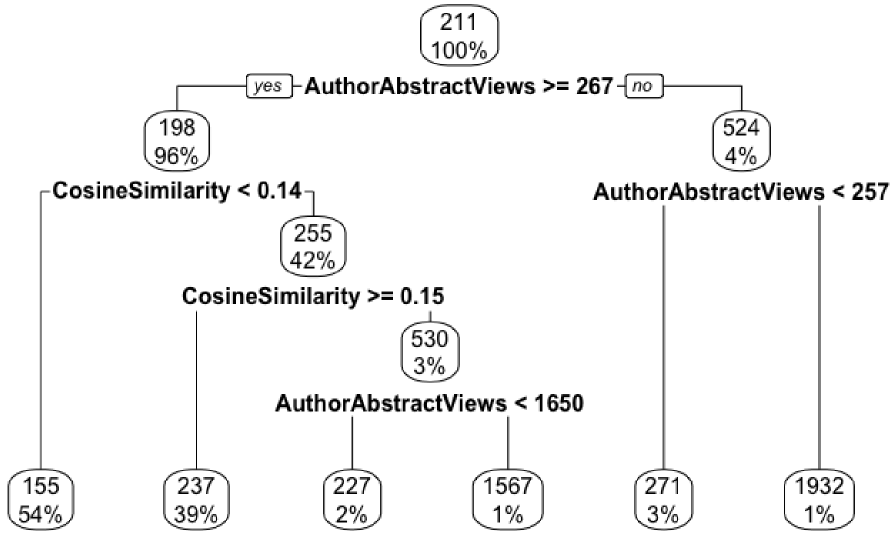


Figure EC.13 An example of a decision tree in the random forest model. The numbers in each node represent the average value (up) and the fraction of samples (bottom).

a single variable determines whether the left or right child node is considered next. When a terminal node (a leaf) is reached, a prediction is returned. For example, the right most leaf contains two values, 1932 and 1%. This means that 1% of the sample satisfies the condition that their author abstract views are less than 257, and the predicted value, e.g., word count, for the sample in this node is 1932.

A random forest procedure uses the following steps (**?**):

1. Choose a bootstrap sample of the observations and start to grow a tree.
2. At each node of the tree, choose a random sample of the features to make the next decision.
3. Repeat this procedure many times to grow a forest of trees.
4. In order to determine the classification of a new observation, have each tree make a classification and use a majority vote for the final prediction.

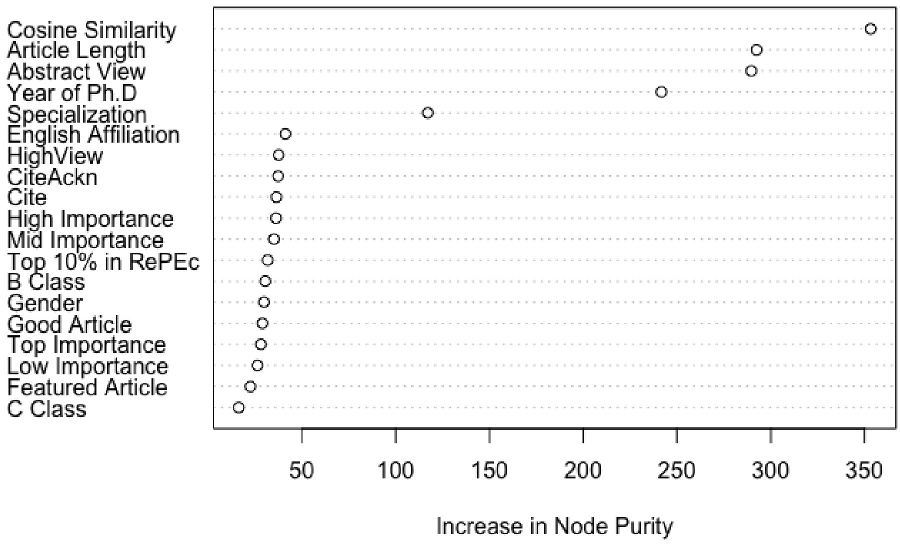


Figure EC.14 **Feature importance in predicting the helpfulness of expert comments. The horizontal axis indicates the increase in node purity of the leaves in the random forest prediction when a feature is considered for splitting the tree (Sample size: 1,188).**

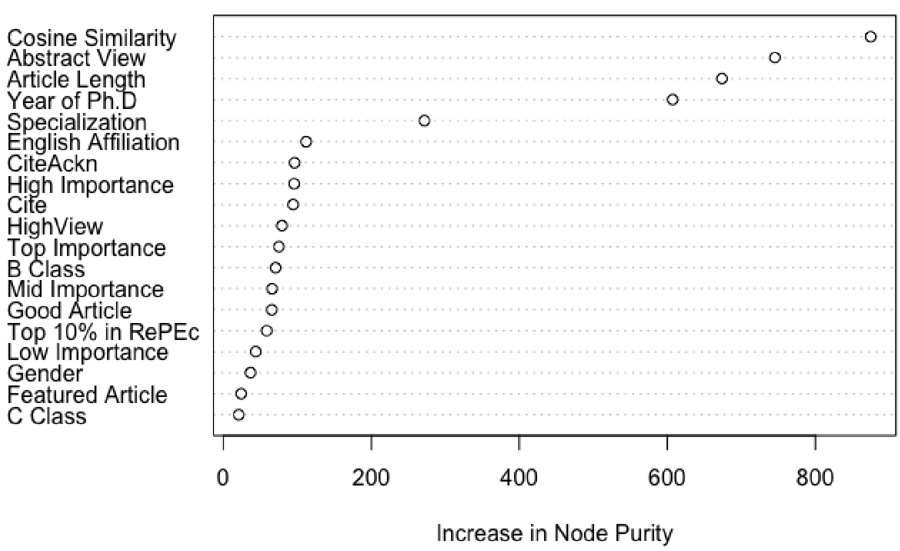


Figure EC.15 **Feature importance in predicting the number of subcomments. The horizontal axis indicates the increase in node purity of the leaves in the random forest prediction when a feature is considered for splitting the tree (Sample size: 1,188).**

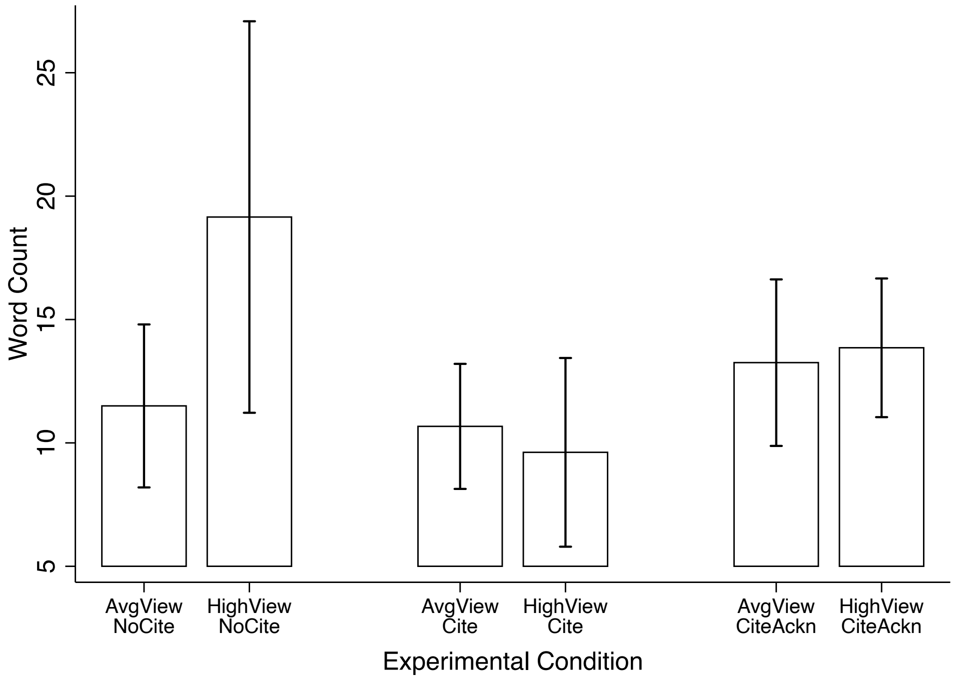


Figure EC.16 Average contribution length by experimental condition (conditional on having made at least one comment): Error bars denote one standard error of the mean (Sample size: 1,188)

EC.4.2.4. Conditional Analyses of Contribution Length and Quality We present regression analyses of contribution length and quality, conditional on an expert having responded positively in the first stage (length), or having made at least one comment (quality).

Contribution Length. Table EC.8 presents four specifications. Columns (1) and (3) report the results from the OLS model, whereas columns (2) and (4) report the results from the exponential dispersion model. Specification (3) in Table EC.8 indicates that the effect of cosine similarity on log(1 + Word Count) is 1.768, which means that comment length grows by 18.2% in response to a one standard deviation increase in cosine similarity.[10] Similarly, a one standard deviation increase from the mean author abstract views is associated with a 4.9% increase in contribution length.

Table EC.9 presents a robustness check for Table EC.8, using percentile of article length and abstract views instead of their log transformation. The regression results in both Tables EC.8 and EC.9 indicate statistically significant and economically sizeable correlations between match quality (cosine similarity) and the length of their comments, which is consistent with Result **??**.

[10] The relative change in word count is calculated as $\Delta(\text{Word Count}\%) = \exp\left\{\hat{\beta}_x \cdot \text{sd}(x)\right\} - 1$, using the $\hat{\beta}_x$ estimated in column (3) of Table EC.8.

Table EC.8 Determinants of Contribution Length (Conditional): Log Article Length and Abstract Views

Dependent Variable:	log(1 + Word Count)			
	(1)	(2)	(3)	(4)
Model Specification	OLS	Exp. Disp.	OLS	Exp. Disp.
HighView	-0.034	0.066	-0.051	0.030
	(0.100)	(0.214)	(0.101)	(0.216)
Cite	-0.070	-0.086	-0.085	-0.119
	(0.096)	(0.210)	(0.097)	(0.213)
CiteAckn	-0.069	-0.047	-0.086	-0.086
	(0.096)	(0.209)	(0.098)	(0.213)
HighView × Cite	-0.072	-0.202	-0.059	-0.176
	(0.137)	(0.299)	(0.138)	(0.302)
HighView × CiteAckn	0.131	0.147	0.149	0.175
	(0.138)	(0.295)	(0.139)	(0.299)
Cosine Similarity			1.768***	2.861***
			(0.166)	(0.360)
log(Article Length)			-0.040	-0.166
			(0.027)	(0.186)
log(1 + Abstract Views)			0.053**	0.083
			(0.032)	(0.069)
English Affiliation			0.095**	0.155
			(0.057)	(0.123)
HighView + HighView × Cite	-0.105	-0.137	-0.110	-0.146
	(0.093)	(0.208)	(0.094)	(0.211)
Cite + HighView × Cite	-0.142	-0.289	-0.144	-0.295
	(0.097)	(0.212)	(0.098)	(0.215)
HighView + HighView × CiteAckn	0.098	0.213	0.097	0.205
	(0.095)	(0.203)	(0.096)	(0.207)
CiteAckn + HighView × CiteAckn	0.062	0.100	0.063	0.089
	(0.098)	(0.207)	(0.099)	(0.209)
Observations (# recommended articles)	8,819	8,819	8,635	8,635

Notes. The dependent variable is the log transformation of word count. Columns (1) and (3) report the results from the OLS model and columns (2) and (4) report the results from the exponential dispersion model. Quality class and importance class are controlled for in all specifications. Fixed effects are included. Standard errors in parentheses are clustered at the expert level. *, ** and *** denote significance level at 10%, 5% and 1% level. The number of observations is the total number of recommended Wikipedia articles to experts who responded positively in the first stage.

Table EC.9 Determinants of Contribution Length (Conditional): Percentile of Article Length and Abstract Views

Dependent Variable:	log(1 + Word Count)			
	(1)	(2)	(3)	(4)
Model Specification	OLS	Exp. Disp.	OLS	Exp. Disp.
HighView	-0.034	0.066	-0.051	0.030
	(0.100)	(0.214)	(0.101)	(0.216)
Cite	-0.070	-0.086	-0.086	-0.119
	(0.096)	(0.210)	(0.097)	(0.213)
CiteAckn	-0.069	-0.047	-0.085	-0.086
	(0.096)	(0.209)	(0.098)	(0.213)
HighView × Cite	-0.072	-0.202	-0.058	-0.176
	(0.137)	(0.299)	(0.138)	(0.302)
HighView × CiteAckn	0.131	0.147	0.147	0.175
	(0.138)	(0.295)	(0.139)	(0.299)
Cosine Similarity			1.768***	2.861***
			(0.166)	(0.360)
Percentile of Article Length			-0.116*	-0.166
			(0.080)	(0.186)
Percentile of Abstract Views			0.154*	0.213
			(0.099)	(0.217)
English Affiliation			0.097**	0.155
			(0.057)	0.123
HighView + HighView × Cite	-0.105	-0.137	-0.108	-0.146
	(0.093)	(0.208)	(0.094)	(0.211)
Cite + HighView × Cite	-0.142	-0.289	-0.144	-0.295*
	(0.097)	(0.212)	(0.098)	(0.215)
HighView + HighView × CiteAckn	0.098	0.213	0.097	0.205
	(0.095)	(0.203)	(0.096)	(0.207)
CiteAckn + HighView × CiteAckn	0.062	0.100	0.063	0.089
	(0.098)	(0.207)	(0.099)	(0.209)
Observations (# of recommended articles)	8,819	8,819	8,635	8,635

Notes. The dependent variable is the log transformation of word count. Columns (1) and (3) report the results from the OLS model, and columns (2) and (4) report the results from the exponential dispersion model. Quality class and importance class are controlled for in all specifications. Fixed effects are controlled for at the expert level. Standard errors in parentheses are clustered at the expert level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Contribution Quality. We now present regression analysis of determinants of contribution quality, conditional on having made at least one comment.

Table EC.10 shows that the effect of CiteAckn on the proportional odds ratio for the ordered logistic model is significantly larger than 1. Put differently, the comments from the CiteAckn conditions are significantly more likely to receive a higher rating for overall quality than the no citation base rate. Results reported in Table EC.10 are robust when we use the percentile of article length and abstract view (Table EC.11), and when we report the ordered logit model for each quality category for overall quality (Table EC.12), helpfulness (Table EC.13) and the number of sub-comments contained in a contribution (Table EC.14). For example, the estimated marginal effect on the probability of be rated as 6 out of 7 is 3.38 p.p. in the AvgView condition ($p < 0.01$) and 3.32 p.p. in the HighView condition ($p < 0.05$) (Table EC.12). Our results also speak to the quality measured by helpfulness (column 3-4 in Table EC.10). Table EC.13 shows that the average marginal effect of CiteAckn is significantly positive (negative) on the probability that the helpfulness of the comment is rated above (below) 4.

Consistent with Result **??**, better match quality between experts and Wikipedia articles improves the quality of contributions. Column (2) in Table EC.10 shows that a unit increase in the cosine similarity measure is associated with an increase of 11.90 in the odds ratio of overall quality. This represents, for example, an increase of 16 p.p. in the probability of being rated 6 ($p < 0.01$) and an increase of 7 p.p. in the probability of being rated 7 ($p < 0.01$). Similarly, columns (4) and (6) provide evidence on the positive impact of cosine similarity on the helpfulness and number of sub-comments. The coefficient on the odds ratio of helpfulness is 14.66 ($p < 0.01$) and the coefficient on the incidence-rate ratio is 3.42 ($p < 0.01$). Our result indicates that contribution quality depend on the matching quality between the specific public good and the contributors' attributions. This finding reinforces prior results in **?**, who shows that the specialization level of a Google Answers contributor has a positive effect on the quality of her answers.

Table EC.11 provides robustness checks for Table EC.10 when we replace the logrithmic transformation by percentile of article length and abstract view. We find that the estimated marginal effect on the probability of be rated as 6 out of 7 is 3.38 p.p. in the AvgView condition ($p < 0.01$) and 3.32 p.p. in the HighView condition ($p < 0.05$). Tables EC.13 and EC.14 provide a complete ordered probit analysis providing robustness checks for helpfulness (see column 3-4 in Table EC.10) and the number of sub-comments, respectively. We find that the average marginal effect of CiteAckn is significantly positive (negative) on the probability that the helpfulness of the comment is rated above (below) 4, whereas the impact of CiteAckn on the number of sub-comments is positive but weakly significant.

Table EC.10 Determinants of Contribution Quality (Conditional): Log Article Length and Abstract Views

Dependent Variable:	Overall Quality		Helpfulness		# of Sub-comments	
	(1)	(2)	(3)	(4)	(5)	(6)
Model Specification	Ordered Logistic		Ordered Logistic		Poisson	
HighView	0.870	0.899	0.846	0.868	0.885	0.898
	(0.222)	(0.232)	(0.218)	(0.228)	(0.105)	(0.107)
Cite	0.877	0.868	0.815	0.806	0.900	0.894
	(0.195)	(0.200)	(0.179)	(0.181)	(0.094)	(0.094)
CiteAckn	1.498**	1.565**	1.346	1.432*	1.094	1.119
	(0.295)	(0.321)	(0.283)	(0.311)	(0.122)	(0.123)
HighView × Cite	1.403	1.429	1.642*	1.701**	1.122	1.139
	(0.493)	(0.508)	(0.561)	(0.588)	(0.178)	(0.179)
HighView × CiteAckn	1.058	1.020	1.239	1.152	1.045	1.008
	(0.346)	(0.347)	(0.412)	(0.396)	(0.159)	(0.154)
Cosine Similarity		11.904***		14.655***		3.421***
		(7.912)		(9.350)		(0.917)
log(Article Length)		1.062		1.084		1.074
		(0.115)		(0.114)		(0.048)
log(1 + Abstract Views)		0.957		1.007		0.999
		(0.076)		(0.083)		(0.035)
English Affiliation		1.021		1.132*		0.999
		(0.146)		(0.158)		(0.063)
HighView + HighView × Cite	1.220	1.285	1.388	1.476*	0.993	1.022
	(0.293)	(0.321)	(0.311)	(0.335)	(0.104)	(0.107)
Cite + HighView × Cite	1.230	1.241	1.337	1.372	1.011	1.018
	(0.334)	(0.337)	(0.350)	(0.360)	(0.121)	(0.117)
HighView + HighView × CiteAckn	0.920	0.917	1.048	1.000	0.924	0.905
	(0.188)	(0.204)	(0.220)	(0.222)	(0.088)	(0.085)
CiteAckn + HighView × CiteAckn	1.584*	1.596*	1.668**	1.650*	1.143	1.129*
	(0.417)	(0.433)	(0.431)	(0.438)	(0.119)	(0.117)
Observations (# comments)	1,097	1,078	1,097	1,078	1,097	1,078

Notes. Columns (1)-(4) report the odds ratio estimated from ordered logistic regressions. Columns (5)-(6) report the incidence-rate ratio estimated from Poisson regressions. Quality class and importance class are controlled for in all specifications. Fixed effects are included. Standard errors in parentheses are clustered at the expert level. *, ** and *** denote significance level at the 10%, 5% and 1% level, respectively. Of the 1,188 comments provided by the experts, 1,097 remain after inappropriate comments are removed. The number of observations further drops to 1,078 after we remove experts without institutional affiliation information.

The regression results in Tables EC.10 and EC.11 indicate economically and statistically significant correlations between the CiteAcknowledge channels and cosine similarity with the quality of expert comments, whereas article length is only significantly correlated with the number of sub-comments in Table EC.11. The latter is somewhat mechanical in the sense that if the article is longer, there is more to comment on.

Lastly, even though experts do not cite themselves often in the entire experiment (mean = 0.374, median = 0), those from the Cite and CiteAck channels do so more frequently (Table EC.15), indicating that at least some contributions are "motivated." Experts from the CiteAck channel are also more likely to provide higher quality comments, indicating that public acknowledgement increases accountability.

Figure EC.16 presents the average word counts of the comments for each experimental condition conditional on having made at least one comment, with the error bars denoting one standard error

Table EC.11 Determinants of Contribution Quality (Conditional): Percentile of Article Length and Abstract Views

Dependent Variable:	Overall Quality		Helpfulness		# of Sub-comments	
	(1)	(2)	(3)	(4)	(5)	(6)
Model Specification	Ordered Logistic		Ordered Logistic		Poisson	
HighView	0.870	0.899	0.846	0.868	0.885	0.898*
	(0.222)	(0.232)	(0.218)	(0.228)	(0.105)	(0.107)
Cite	0.877	0.868	0.815	0.805	0.900	0.893
	(0.195)	(0.200)	(0.179)	(0.181)	(0.094)	(0.094)
CiteAckn	1.498**	1.572**	1.346	1.444*	1.094	1.124
	(0.295)	(0.324)	(0.283)	(0.313)	(0.122)	(0.124)
HighView × Cite	1.403	1.432	1.642	1.706	1.122	1.141
	(0.493)	(0.510)	(0.561)	(0.590)	(0.178)	(0.179)
HighView × CiteAckn	1.058	1.012	1.239	1.142	1.045	1.003
	(0.346)	(0.344)	(0.412)	(0.393)	(0.159)	(0.153)
Cosine Similarity		11.983***		14.789***		3.422***
		(7.970)		(9.441)		(0.914)
Percentile of Article Length		1.063		1.086		1.075
		(0.115)		(0.114)		(0.048)
Percentile of Abstract Views		0.933		1.109		1.051
		(0.232)		(0.275)		(0.121)
English Affiliation		1.017		1.128		0.998
		(0.144)		(0.156)		(0.063)
HighView + HighView × Cite	1.220	1.286	1.388	1.481*	0.993	1.025
	(0.293)	(0.320)	(0.311)	(0.336)	(0.104)	(0.107)
Cite + HighView × Cite	1.230	1.243	1.337	1.373	1.011	1.019
	(0.334)	(0.337)	(0.350)	(0.361)	(0.121)	(0.118)
HighView + HighView × CiteAckn	0.920	0.910	1.048	0.992	0.924	0.901*
	(0.188)	(0.201)	(0.220)	(0.219)	(0.088)	(0.085)
CiteAckn + HighView × CiteAckn	1.584*	1.591*	1.668**	1.649**	1.143	1.128**
	(0.417)	(0.432)	(0.431)	(0.437)	(0.119)	(0.117)
Observations (# comments)	1,097	1,078	1,097	1,078	1,097	1,078

Notes. Columns (1)-(4) report odds ratios estimated from ordered logistic regressions. Columns (5) and (6) report incidence-rate ratios estimated from Poisson regressions. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the expert level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

($n = 1,188$ comments from 512 experts). Interesting, the high view with no citation treatment generates significant longer comments compared to the baseline, which is likely due to selection.

Figure EC.17 plots the average overall quality of the comments for each experimental condition, with the error bars denoting one standard error. We see that experts coming into the second stage from the Cite-Acknowledgement channels provide higher quality comments, possibly due to social image concerns (**?**).

Table EC.12 Average Marginal Effect on Overall Quality (Conditional)

Dependent Variable:	Overall Quality						
	$P(Y=1)$	$P(Y=2)$	$P(Y=3)$	$P(Y=4)$	$P(Y=5)$	$P(Y=6)$	$P(Y=7)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Specification	Ordered Logistic						
HighView	0.007	0.009	0.008	-0.000	-0.014	-0.007	-0.003
	(0.018)	(0.021)	(0.020)	(0.002)	(0.035)	(0.016)	(0.007)
Cite	0.010	0.011	0.011	-0.001	-0.019	-0.009	-0.004
	(0.016)	(0.019)	(0.018)	(0.002)	(0.031)	(0.014)	(0.006)
CiteAckn	-0.024**	-0.031**	-0.038**	-0.013*	0.057**	0.034**	0.015**
	(0.012)	(0.015)	(0.018)	(0.008)	(0.026)	(0.016)	(0.008)
HighView × Cite	-0.024	-0.028	-0.029	0.000	0.048	0.023	0.010
	(0.024)	(0.029)	(0.028)	(0.004)	(0.049)	(0.022)	(0.010)
HighView × CiteAckn	-0.003	-0.003	-0.001	0.004	0.004	-0.001	-0.001
	(0.021)	(0.025)	(0.028)	(0.010)	(0.044)	(0.020)	(0.011)
Cosine Similarity	-0.149***	-0.184***	-0.203***	-0.037**	0.322***	0.174***	0.078***
	(0.045)	(0.053)	(0.037)	(0.021)	(0.085)	(0.048)	(0.023)
log(Article Length)	-0.004	-0.004	-0.005	-0.001	0.008	0.004	0.002
	(0.006)	(0.008)	(0.009)	(0.002)	(0.014)	(0.007)	(0.003)
log(1 + Abstract Views)	0.003	0.003	-0.004	0.001	-0.006	-0.003	-0.001
	(0.005)	(0.006)	(0.007)	(0.001)	(0.010)	(0.006)	(0.002)
English Affiliation	-0.001	-0.008	-0.002	-0.000	0.003	0.001	0.001
	(0.007)	(0.007)	(0.012)	(0.002)	(0.019)	(0.010)	(0.003)
HighView + HighView × Cite	-0.017	-0.020	-0.020	-0.000	0.034	0.016	0.007
	(0.017)	(0.020)	(0.020)	(0.004)	(0.034)	(0.016)	(0.007)
Cite + HighView × Cite	-0.014	-0.017	-0.018	-0.001	0.029	0.014	0.006
	(0.018)	(0.022)	(0.022)	(0.003)	(0.037)	(0.017)	(0.007)
HighView + HighView × CiteAckn	0.004	0.005	0.007	0.004	-0.010	-0.007	-0.003
	(0.010)	(0.014)	(0.019)	(0.011)	(0.026)	(0.019)	(0.009)
CiteAckn + HighView × CiteAckn	-0.027	-0.035	-0.039*	-0.008	0.061**	0.033*	0.015*
	(0.017)	(0.021)	(0.022)	(0.008)	(0.036)	(0.019)	(0.008)
Observations (# comments)	1078						

Notes. Columns (1)-(7) report the average marginal effects on the probability that median overall quality receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the expert level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.13 Average Marginal Effect on Helpfulness (Conditional)

Dependent Variable:	Helpfulness						
	P($Y=1$)	P($Y=2$)	P($Y=3$)	P($Y=4$)	P($Y=5$)	P($Y=6$)	P($Y=7$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Specification	Ordered Logistic						
HighView	0.010	0.010	0.011	0.003	-0.017	-0.011	-0.005
	(0.020)	(0.018)	(0.019)	(0.005)	(0.032)	(0.021)	(0.009)
Cite	0.016	0.015	0.016	0.004	-0.026	-0.017	-0.007
	(0.017)	(0.016)	(0.016)	(0.005)	(0.027)	(0.018)	(0.008)
CiteAckn	-0.021	-0.022	-0.027	-0.017	0.038	0.033*	0.016
	(0.013)	(0.013)	(0.017)	(0.011)	(0.023)	(0.020)	(0.010)
HighView × Cite	-0.038	-0.036	-0.040	-0.013	0.063	0.043	0.019
	(0.026)	(0.024)	(0.025)	(0.009)	(0.042)	(0.028)	(0.013)
HighView × CiteAckn	-0.010	-0.010	-0.011	-0.003	0.017	0.011	0.005
	(0.023)	(0.022)	(0.026)	(0.015)	(0.038)	(0.031)	(0.015)
Cosine Similarity	-0.175***	-0.169***	-0.200***	-0.098***	0.295***	0.235***	0.111***
	(0.048)	(0.044)	(0.048)	(0.029)	(0.071)	(0.056)	(0.031)
log(Article Length)	-0.005	-0.005	-0.006	-0.003	0.009	0.007	0.003
	(0.007)	(0.007)	(0.008)	(0.004)	(0.012)	(0.009)	(0.004)
log(1 + Abstract Views)	-0.000	-0.000	-0.001	-0.000	0.001	0.001	0.000
	(0.005)	(0.005)	(0.006)	(0.003)	(0.009)	(0.007)	(0.003)
English Affiliation	-0.008	-0.008	-0.009	-0.005	0.014	0.011	0.005
	(0.009)	(0.009)	(0.010)	(0.005)	(0.015)	(0.012)	(0.006)
HighView + HighView × Cite	-0.027*	-0.026*	-0.029*	-0.010	0.046*	0.032*	0.014
	(0.016)	(0.016)	(0.017)	(0.008)	(0.027)	(0.019)	(0.009)
Cite + HighView × Cite	-0.022	-0.021	-0.024	-0.010	0.037	0.027	0.012
	(0.019)	(0.018)	(0.019)	(0.008)	(0.031)	(0.022)	(0.010)
HighView + HighView × CiteAckn	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.011)	(0.012)	(0.017)	(0.014)	(0.020)	(0.022)	(0.012)
CiteAckn + HighView × CiteAckn	-0.032**	-0.031*	-0.038**	-0.020*	0.055*	0.044*	0.021*
	(0.018)	(0.018)	(0.020)	(0.011)	(0.020)	(0.023)	(0.011)
Observations (# comments)	1078						

Notes. Columns (1)-(7) report the average marginal effects on the probability that median helpfulness receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the expert level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.14 Average Marginal Effect on # of Sub-comments (Conditional)

Model Specification	Poisson
Dependent Variable:	# of Sub-comments
HighView	-0.288
	(0.317)
Cite	-0.297
	(0.285)
CiteAckn	0.335
	(0.325)
HighView × Cite	0.343
	(0.411)
HighView × CiteAckn	-0.010
	(0.428)
Cosine Similarity	3.364***
	(0.755)
log(Article Length)	0.195
	(0.122)
log(1 + Abstract Views)	-0.002
	(0.095)
English Affiliation	-0.002
	(0.172)
HighView + HighView × Cite	0.056
	(0.268)
Cite + HighView × Cite	0.046
	(0.294)
HighView + HighView × CiteAckn	-0.298
	(0.286)
CiteAckn + HighView × CiteAckn	0.324
	(0.234)
Observations (# comments)	1078

Notes. Columns (1)-(7) report the average marginal effects on the number of subcomments receives the corresponding score. Quality class and importance class are controlled for in all specifications. Standard errors in parentheses are clustered at the expert level. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Table EC.15 Determinants of Self-citation (Conditional)

Dependent Variable:	# of Self-citations	
HighView	1.925*	1.979*
	(0.836)	(0.817)
Cite	2.833***	2.681***
	(0.929)	(0.906)
CiteAckn	3.201***	2.816**
	(1.130)	(0.960)
HighView × Cite	0.453	0.470
	(0.245)	(0.248)
HighView × CiteAckn	0.531	0.527
	(0.291)	(0.262)
Cosine Similarity		10.838***
		(7.175)
log(Article Length)		1.255
		(0.182)
log(1 + Abstract Views)		1.508***
		(0.190)
English Affiliation		0.846
		(0.172)
HighView + HighView × Cite	0.871	0.930
	(0.281)	(0.291)
Cite + HighView × Cite	1.282	1.260
	(0.551)	(0.535)
HighView + HighView × CiteAckn	1.023	1.042
	(0.340)	(0.315)
CiteAckn + HighView × CiteAckn	1.701	1.483*
	(0.710)	(0.553)
Observations (# comments)	1,097	1,078

Notes. The two columns report the incidence-rate ratio estimated from Poisson regressions. Quality class and importance class are controlled for in all specifications. Fixed effects are included. Standard errors in parentheses are clustered at the expert level. *, ** and *** denote significance level at the 10%, 5% and 1% level, respectively. Of the 1,188 comments provided by the experts, 1,097 remain after inappropriate comments are removed. The number of observations further drops to 1,078 after we remove experts without institutional affiliation information.

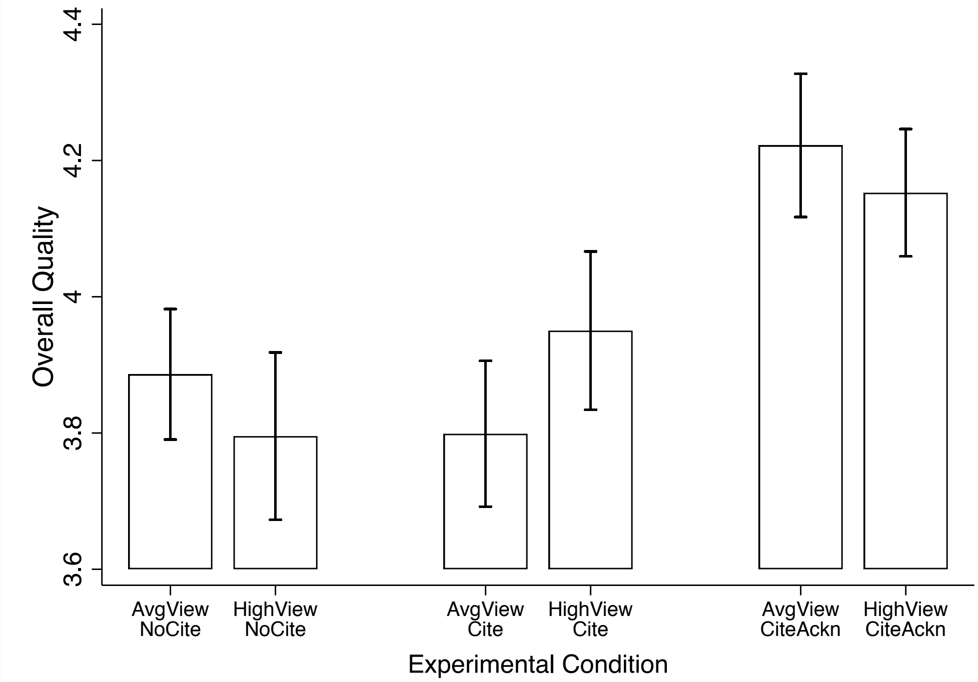


Figure EC.17 Average overall quality by experimental condition (conditional on having made at least one comment): Error bars denote one standard error of the mean (Sample size: 1,188)

EC.5. Rating protocol

Below we provide the rating protocol instructions. For each rating question, we also provide the mean, median and standard deviation.

Welcome to this rating session. Before you rate each comment, please read the associated Wikipedia article first.

- Suppose that you are to incorporate the expert's review of this Wikipedia article and you want to break down the review into multiple pieces of comments. How many pieces of comments has the expert made to this Wikipedia article? (mean: 2.711, median: 2, standard deviation: 0.069)
- According to the expert, this Wikipedia article has

  ____ errors (mean: 1.444, median: 0, standard deviation: 0.912)

  ____ missing points (mean: 1.098, median: 1, standard deviation: 0.040)

  ____ missing references (mean: 0.626, median: 0, standard deviation: 0.049)

  ____ outdated information (mean: 0.043, median: 0, standard deviation: 0.007)

  ____ outdated references (mean: 0.010, median: 0, standard deviation: 0.003)

  ____ irrelevant information (mean: 0.134, median: 0, standard deviation: 0.013)

  ____ irrelevant references (mean: 0.016, median: 0, standard deviation: 0.005)

  ____ other issues. (mean: 0.238, median: 0, standard deviation: 0.019) Please specify: ______________
- How many references does the expert provide for the Wikipedia article?____ (mean: 1.508, median: 0, standard deviation: 0.074)
- How many self-cited references does the expert provide for the Wikipedia article? ____ (mean: 0.374, median: 0, standard deviation: 0.032)
- Rate the amount of effort needed to address the experts' comments. (1 = cut and paste; 7 = rewrite the entire article) (mean: 3.621, median: 4, standard deviation: 0.057)
- Rate the amount of expertise needed to address the experts' comments. (1 = high school AP economics classes; 7 = PhD in economics) (mean: 3.887, median: 4, standard deviation: 0.057)
- How easily can the issues raised in the comment be located in the Wikipedia article? (1 = unclear where to modify in the Wikipedia article; 7 = can be identified at the sentence level) (mean: 4.572, median: 5, standard deviation: 0.061)
- Suppose you are to incorporate this expert's comments. How helpful are they? (1 = not helpful at all; 7 = very helpful) (mean: 4.121, median: 4, standard deviation: 0.045)
- Please rate the overall quality of the comment. (1 = not helpful at all; 7 = extremely helpful) (mean: 3.968, median: 4, standard deviation: 0.044)

EC.6. Cosine similarity

In this appendix, we describe the process used to compute the cosine similarity between two documents, an expert's abstract and a Wikipedia article. Cosine similarity of two documents measures the similarity between them in terms of overlapping vocabulary.

1. Retrieving two pieces of text:
   (a) Document a is the abstract of **?**:

   "This paper considers how identity, a person's sense of self, affects economic outcomes. We incorporate the psychology and sociology of identity into an economic model of behavior. In the utility function we propose, identity is associated with different social categories and how people in these categories should behave. We then construct a simple game-theoretic model showing how identity can affect individual interactions. The paper adapts these models to gender discrimination in the workplace, the economics of poverty and social exclusion, and the household division of labor. In each case, the inclusion of identity substantively changes conclusions of previous economic analysis."

   (b) Document b is the Wikipedia article on Identity Economics (`https://en.wikipedia.org/wiki/Identity_economics`, accessed on April 27, 2022), with only the text part of the article retrieved from the MediaWiki API on December 2, 2018.

   "Identity economics Identity economics captures the idea that people make economic choices based on both monetary incentives and their identity: holding monetary incentives constant, people avoid actions that conflict with their concept of self. The fundamentals of identity economics was first formulated by Nobel Prize–winning economist George Akerlof and Rachel Kranton in their article "Economics and Identity," [1] published in Quarterly Journal of Economics. This article provides a framework for incorporating social identities into standard economics models, expanding the standard utility function to include both pecuniary payoffs and identity utility. The authors demonstrate the importance of identity in economics by showing how predictions of the classic principal-agent problem change when the identity of the agent is considered. Akerlof and Kranton provide an overview of their work in the book "Identity Economics," [2] published in 2010. In the book, they provide a layman's approach to Identity Economics and apply the concept to workplace organization, gender roles, and educational choice, summarizing several previous papers on the applications of Identity Economics. [3][4][5] While this macro-economic theory deals exclusively with already well established categories of social identity, Laszlo Garai when applied the concept of social identity in economic psychology [6] takes into consideration identities in statu nascendi (i.e. in the course of being formed and developed). [7][8] This theory that is referred to the macro-processes based on a "large-scale production" later gets applied to the individual creativity's psychology: Garai derived it from the principal's and, resp., agent's "identity elaboration". A further special feature of Garai's theory on social identity is that it resolved the contradiction between the inter-individual phenomena studied by the social identity theories and the intraindividual mechanisms studied by the brain theories: L. Garai presented [9] a theory on an inter-individual mechanism acting in the world of social identity. The theory that was referred in the beginning to the macro-processes based on a large-scale production later has been applied by Garai to the micro-processes of individual creativity. [10] Following papers have used social identity to examine a variety of subjects within economics. Moses Shayo uses the concept of social identity to explain why countries with similar economic characteristics might choose substantially different levels of redistribution. [11] The paper won the 2009 Michael Wallerstein Award, given to the best article published in the area of political economy. Daniel Benjamin, James Choi, and Joshua Strickland examine the effect of social identity, focusing on ethnic identity, on a wide range of economic behavior. [12] For a review of papers that study economics and identity, see articles by Claire Hill (2007) and John Davis (2004). [13][14]"

2. Filtering the text: remove all the non-alphabetic characters from Documents a and b. Document a becomes:

   "This paper considers how identity a person s sense of self affects economic outcomes We incorporate the psychology and sociology of identity into an economic model of behavior In the utility function we propose identity is associated with different social categories and how people in these categories should behave We then construct a simple game theoretic model showing how identity can affect individual interactions The paper adapts these models to gender discrimination in the workplace the economics of poverty and social exclusion and the household division of labor In each case the inclusion of identity substantively changes conclusions of previous economic analysis"

3. Tokenizing: enter both text files into a tokenizer, which divides text into a sequence of tokens, which roughly correspond to words. Document a becomes the following list of tokens:

   ['This', 'paper', 'considers', 'how', 'identity', 'a', 'person', 's', 'sense', 'of', 'self', 'affects', 'economic', 'outcomes', 'We', 'incorporate', 'the', 'psychology', 'and', 'sociology', 'of', 'identity', 'into', 'an', 'economic', 'model', 'of', 'behavior', 'In', 'the', 'utility', 'function', 'we', 'propose', 'identity', 'is', 'associated', 'with', 'different', 'social', 'categories', 'and', 'how', 'people', 'in', 'these', 'categories', 'should', 'behave', 'We', 'then', 'construct', 'a', 'simple', 'game', 'theoretic', 'model', 'showing', 'how', 'identity', 'can', 'affect', 'individual', 'interactions', 'The', 'paper', 'adapts', 'these', 'models', 'to', 'gender', 'discrimination', 'in', 'the', 'workplace', 'the', 'economics', 'of', 'poverty', 'and', 'social', 'exclusion', 'and', 'the', 'household', 'division', 'of', 'labor', 'In', 'each', 'case', 'the', 'inclusion', 'of', 'identity', 'substantively', 'changes', 'conclusions', 'of', 'previous', 'economic', 'analysis']

4. Removing stop words: make all the characters lower-case and remove all the stop words. Document a becomes:

   ['paper', 'considers', 'identity', 'person', 'sense', 'self', 'affects', 'economic', 'outcomes', 'incorporate', 'psychology', 'sociology', 'identity', 'economic', 'model', 'behavior', 'utility', 'function', 'propose', 'identity', 'associated', 'different', 'social', 'categories', 'people', 'categories', 'behave', 'construct', 'simple', 'game', 'theoretic', 'model', 'showing', 'identity', 'affect', 'individual', 'interactions', 'paper', 'adapts', 'models', 'gender', 'discrimination', 'workplace', 'economics', 'poverty', 'social', 'exclusion', 'household', 'division', 'labor', 'case', 'inclusion', 'identity', 'substantively', 'changes', 'conclusions', 'previous', 'economic', 'analysis']

5. Stemming: convert each token to its corresponding stem, which strips variants of the same word into the word's root. Document a becomes:

   ['paper', 'consid', 'ident', 'person', 'sens', 'self', 'affect', 'econom', 'outcom', 'incorpor', 'psycholog', 'sociolog', 'ident', 'econom', 'model', 'behavior', 'util', 'function', 'propos', 'ident', 'associ', 'differ', 'social', 'categori', 'peopl', 'categori', 'behav', 'construct', 'simpl', 'game', 'theoret', 'model', 'show', 'ident', 'affect', 'individu', 'interact', 'paper', 'adapt', 'model', 'gender', 'discrimin', 'workplac', 'econom', 'poverti', 'social', 'exclus', 'household', 'divis', 'labor', 'case', 'inclus', 'ident', 'substant', 'chang', 'conclus', 'previou', 'econom', 'analysi']

6. Defining the stemmed corpus: take the union of the two stemmed documents, where each unique stemmed token is defined as a dimension.

   stemmed-corpus = ['paper', 'consid', 'ident', 'person', 'sens', 'self', 'affect', 'econom', 'outcom', 'incorpor', 'psycholog', 'sociolog', 'model', 'behavior', 'util', 'function', 'propos', 'associ', 'differ', 'social', 'categori', 'peopl', 'behav', 'construct', 'simpl', 'game', 'theoret', 'show', 'individu', 'interact', 'adapt', 'gender', 'discrimin', 'workplac', 'poverti', 'exclus', 'household', 'divis', 'labor', 'case', 'inclus', 'substant', 'chang', 'conclus', 'previou', 'analysi', 'captur', 'idea', 'make', 'choic', 'base', 'monetari', 'incent', 'hold', 'constant', 'avoid', 'action', 'conflict', 'concept', 'fundament', 'first', 'formul', 'nobel', 'prize', 'win', 'economist', 'georg', 'akerlof', 'rachel', 'kranton', 'articl', 'publish', 'quarterli', 'journal', 'provid', 'framework', 'standard', 'expand', 'includ', 'pecuniari', 'payoff', 'author', 'demonstr', 'import', 'predict', 'classic', 'princip', 'agent', 'problem', 'overview', 'work', 'book', 'layman', 'approach', 'appli', 'organ', 'role', 'educ', 'summar', 'sever', 'applic', 'macro', 'theori', 'deal', 'alreadi', 'well', 'establish', 'laszlo', 'garai', 'take', 'consider', 'statu', 'nascendi', 'e', 'cours', 'form', 'develop', 'refer', 'process', 'larg', 'scale', 'product', 'later', 'get', 'creativ', 'deriv', 'resp', 'elabor', 'special', 'featur', 'resolv', 'contradict', 'inter', 'phenomena', 'studi', 'intraindividu', 'mechan', 'brain', 'l', 'present', 'act', 'world', 'begin', 'micro', 'follow', 'use', 'examin', 'varieti', 'subject', 'within', 'mose', 'shayo', 'explain', 'countri', 'similar', 'characterist', 'might', 'choos', 'substanti', 'level', 'redistribut', 'michael', 'wallerstein', 'award', 'given', 'best', 'area', 'polit', 'economi', 'daniel', 'benjamin', 'jame', 'choi', 'joshua', 'strickland', 'effect', 'focus', 'ethnic', 'wide', 'rang', 'review', 'see', 'clair', 'hill', 'john', 'davi']

7. Vectorizing: pass the stemmed corpus to a tf (term frequency) vectorizer, which generates two vectors, one for each document based on the number of token stems included in each piece of text. For example, for Document a, the stem 'paper' appears twice, thus the first entry in vector A is 2. In comparison, the stem 'davi' does not appear at all, so the last entry in A is 0.

   $A =$ [2, 1, 5, 1, 1, 1, 2, 4, 1, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0]

   $B =$ [4, 1, 24, 0, 0, 1, 0, 17, 0, 1, 2, 0, 1, 1, 2, 1, 0, 0, 1, 9, 1, 2, 0, 0, 0, 0, 0, 1, 4, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 2, 3, 2, 2, 1, 1, 1, 1, 1, 4, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 4, 3, 1, 1, 3, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 3, 1, 1, 1, 2, 1, 1, 4, 1, 1, 1, 1, 1, 1, 3, 7, 1, 1, 1, 1, 1, 5, 1, 1, 1, 1, 1, 1, 1, 1, 2, 3, 2, 2, 2, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 1, 3, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]

   In the actual process, we use a tf-idf (term frequency–inverse document frequency) vectorizer (**?**), which further weighs each element in each vector by its frequency in the stemmed corpus (omitted).

8. Calculating the cosine similarity between the two vectors:

$$\cos(\theta) = \frac{\mathbf{A}^T \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} = 0.635.$$