What motivates experts to contribute to public information goods? 
A field experiment at Wikipedia

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*School of Information Sciences, University of Pittsburgh  
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January 2018
Motivation
Literature Review
Experimental Design
Results
Conclusion
User-Generated Content as Public Information Good

- User-generated content
  - Online reviews: Amazon, Yelp
  - Online health support networks: ACS Cancer Support Network
User-Generated Content as Public Information Good

- User-generated content
  - Online reviews: Amazon, Yelp
  - Online health support networks: ACS Cancer Support Network

- Public information goods
  - Non-rivalrous
  - Non-excludable (by choice)
  - Expertise matters: inputs are not perfect substitutes
    - quality
    - marginal cost
    - (affect)
Research Questions

▶ What motivates experts to contribute to public information?

▶ Voluntary contribution to public goods

▶ Free-riding problem

▶ How motivating is social impact?

▶ Number of recipients (Andreoni, 2006 & 2007)

▶ 40% decrease after exogenous reduction in readership in Chinese Wikipedia (Zhang and Zhu, 2011)

▶ How motivating are private benefits?
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  - 5.4 million articles in the English Wikipedia
  - 50,000 high quality articles (March, 2017)
  - More than 500 million unique visitors each month

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  - Experts seldom make contributions (YeckehZaare 2015)

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  - Women: sparse

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- How do we motivate domain experts (scientists, etc.) to contribute?
Example: Instrumental Variable

“. . ., the method of instrumental variables (IV) is used to estimate causal relationships when controlled experiments are not feasible . . .”
Motivation

**Literature Review**
Experimental Design
Results
Conclusion
Literature

- Laboratory and field experiments on public goods
  - Ledyard (1995)
  - Vesterlund (2016): charitable giving

- What motivates Wikipedians (insiders)
  - Reciprocity, social image (Algan et al. 2013)
  - Symbolic awards (Gallus 2016)
  - Better matching and lower cost (Cosley et al. 2007)

- What motivates domain experts (outsiders)
  - Tabarolo, Mietchen, Alevizou and Gill (2011)
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Experimental Design: $2 \times 3$ factorial design

- Social impact
  1. Average view: # of views of a typical WP article (426)
  2. High view: # of views of the recommended articles (> 1,000)
Experimental Design: $2 \times 3$ factorial design

- **Social impact**
  1. Average view: # of views of a typical WP article (426)
  2. High view: # of views of the recommended articles (> 1,000)

- **Private benefits**
  1. No Cite: no citation benefit mentioned
  2. Citation:
     - might cite your work
     - may include some of your publications in their references
     - might refer to some of your research
  3. Citation & acknowledgement:
     - citation
     - acknowledge your contributions publicly
Experimental Design: $2 \times 3$ factorial design

<table>
<thead>
<tr>
<th></th>
<th>No Citation</th>
<th>Citation</th>
<th>Citation &amp; Acknowledge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average View</td>
<td>AvgView-NoCite $(n = 678)$</td>
<td>AvgView-Cite $(n = 669)$</td>
<td>AvgView-CiteAcknowledge $(n = 672)$</td>
</tr>
<tr>
<td>High View</td>
<td>HighView-NoCite $(n = 636)$</td>
<td>HighView-Cite $(n = 661)$</td>
<td>HighView-CiteAcknowledge $(n = 658)$</td>
</tr>
</tbody>
</table>

Total number of participants:

- Intent to treat: $n = 3,974$
- Treated group: $n = 3,288$
Domain experts in this experiment: Academic economists

- Participant information retrieved from RePEc:
  https://ideas.repec.org
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- Why RePEc?
  - Data use policy: http://repec.org/docs/RePEcDataUse.html
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  - RePEc ranking
- Expert selection
  - Post at least six articles in English: 3,974
  - Accuracy of recommender system
Expert selection: Distribution of # of publications on RePEc
Wikipedia article selection

- Under namespace 0 (Main/Article)
- Not edit protected
- Not a “stub”
- At least 1,500 characters
- Viewed at least 1,000 times in the past 30 days (dynamically updated)
Implementation: Three-phase design

- **Phase 1**
  - Send personalized email invitations to experts
  - Treatments implemented

- **Phase 2**
  - Recommend relevant articles to interested experts
  - Articles selected to match experts’ recent work

- **Phase 3**
  - Send thank-you email
  - Links to posted comments on Talk Page
  - Links to tutorial on editing Wikipedia articles
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
Phase 2: Recommending relevant articles

Dear Dr. Bebchuk,

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.

<table>
<thead>
<tr>
<th>Wikipedia Article Title</th>
<th>Number of views in the past month</th>
<th>Link to review the article</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shareholder value</td>
<td>6,298</td>
<td>Click here</td>
</tr>
<tr>
<td>Corporate governance</td>
<td>38,351</td>
<td>Click here</td>
</tr>
<tr>
<td>Managerial economics</td>
<td>17,771</td>
<td>Click here</td>
</tr>
<tr>
<td>Economic nationalism</td>
<td>8,931</td>
<td>Click here</td>
</tr>
<tr>
<td>University of Delaware</td>
<td>17,123</td>
<td>Click here</td>
</tr>
<tr>
<td>Corporatocracy</td>
<td>10,479</td>
<td>Click here</td>
</tr>
</tbody>
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Phase 2: Interface design - lowering entry cost

- Lower entry barrier: no need to learn how to edit wiki
- Separate expert’s comments from incorporation into WP article
Email Sending Procedure

- Emails sent 6:00 AM – 7:00 PM of expert’s local time (based on location of primary affiliation)
- System tracks if each expert opens email
  - 84% opened first email (treated group)
- Responses:
  - Yes: phase 2 email sent immediately
  - No: dropped
  - No response after 2 weeks: 4 reminders
- Comments: manually verified before posting to article Talk page
What happened to these comments?

- **ExpertIdeas Bot**
  - Post comments on article talk page
  - Alert Wikipedia editors who watch this page

- **Three scenarios**
  - Best case: editors incorporate these comments
  - Intermediate case: editors comment on the comments
  - Worst case: nothing happens

- **Students working with Wiki Ed to incorporate these comments**
  - SI 563 (Game Theory)
  - 100% edits stayed after 4 months
Theory

- Public good: $y > 0$
- Number of consumers of this public good: $n \geq 0$
- Contribution level, $a$, from a choice set, $A \in [0, \bar{a})$
- Cost function, $c(a)$, is convex
- Social impact of public goods: $v(n)(y + ay)$
- Private benefit from contributions: $w(n)a$

$$\max_{a \in A} v(n)(y + ay) + w(n)a + \gamma(A - a) - \frac{c(a)}{s}. \quad (1)$$

Assuming $c(a) = ca^2/2$, we obtain optimal contribution level:

$$a^* = [v(n)y + w(n) - \gamma]\frac{s}{c}, \quad (2)$$
Hypotheses

▶ Experts will be more interested to contribute when citation benefit is made salient: $\frac{\partial a^*}{\partial w} = \frac{s}{c} > 0$.

▶ Experts will be more interested to contribute with increasing # of views: $\frac{\partial a^*}{\partial n} = [v'(n)y + w'(n)]\frac{s}{c} > 0$.

▶ An expert with a higher reputation will contribute less: $\frac{\partial a^*}{\partial \gamma} = -\frac{s}{c} < 0$.

▶ Better matching between the content of the public information good and the agent’s expertise leads to an increased level of contributions, i.e., $\frac{\partial a^*}{\partial s} = [v(n)y + w(n) - \gamma]/c \geq 0$ if and only if $v(n)y + w(n) \geq \gamma$. 
Phase 1: Treatment effects on positive response

- NoCite & AvgView (baseline: 45%): high compared to APS campaign
- High View by itself: positive but insignificant effect
- Citation & High View: the highest positive response rate
## Treatment effects: Average marginal effects of multinomial logistic regression on participation

<table>
<thead>
<tr>
<th></th>
<th>Positive</th>
<th>No response</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>HighView</td>
<td>0.002</td>
<td>0.021</td>
<td>-0.022</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Citation</td>
<td>0.040</td>
<td>0.022</td>
<td>-0.064**</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Acknowledgment</td>
<td>0.030</td>
<td>0.019</td>
<td>-0.050*</td>
</tr>
<tr>
<td>((Interaction terms snipped))</td>
<td>(0.029)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>HighView + HighView × Citation</td>
<td>0.022</td>
<td>-0.002</td>
<td>-0.020</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.026)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Citation + HighView × Citation</td>
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<tr>
<td></td>
<td>(0.030)</td>
<td>(0.027)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>HighView + HighView × Acknowledgement</td>
<td>0.018</td>
<td>0.017</td>
<td>-0.036</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.027)</td>
<td>(0.026)</td>
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<tr>
<td>Acknowledgement + HighView × Acknowledgement</td>
<td>0.047</td>
<td>0.016</td>
<td>-0.063**</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.027)</td>
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1. **Citation at HighView** increases positive response by 6 p.p.;
2. **Citation** decreases negative response by 6 p.p. at both views;
Reputation and social distance

<table>
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<td></td>
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<td>-0.050*</td>
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<td>-0.045*</td>
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<td>(0.026)</td>
<td>(0.030)</td>
<td>(0.026)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td><strong>Author Abstract Views</strong></td>
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<td>0.033</td>
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<td>0.384***</td>
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<tr>
<td>(0.188)</td>
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<td></td>
<td></td>
<td>(0.192)</td>
<td>(0.145)</td>
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</tr>
<tr>
<td><strong>English Affiliation</strong></td>
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<td></td>
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<td>-0.017</td>
<td>-0.043***</td>
<td>0.060***</td>
</tr>
<tr>
<td>(0.018)</td>
<td></td>
<td></td>
<td></td>
<td>(0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Behavioral &amp; experimental econ.</strong></td>
<td>0.210***</td>
<td>-0.075***</td>
<td>-0.134***</td>
<td>(0.034)</td>
<td>(0.028)</td>
<td>(0.025)</td>
</tr>
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</table>

1. **Reputation**: A 1,000-view increase in the number of author abstract views is associated with a 0.83 p.p. increase in the likelihood of a negative response. ABV normalized to [0, 1] from [51, 46,057].

2. **Social distance**: Behavioral and experimental economists are 21 (13.5) p.p. more (less) likely to respond positively (negatively) than others.
Samples through Phases 1 and 2

all 3,974 experts contacted by first email

1,605 experts with positive response

1,513 experts opened second email

512 experts commented on at least 1 article
Phase 2: Contribution Quantity

- 1,513 (94%) opened phase-2 email
- 512 (34%) commented on at least one WP article
- 1,190 comments received by November 30, 2016
- Large variance in quantity (word count)
  - Some wrote one-line comments
  - Some rewrote the entire article

Table: Participants’ responses in Phase 2, by experimental conditions

<table>
<thead>
<tr>
<th></th>
<th>AvgView NoCite</th>
<th>AvgView Cite</th>
<th>AvgView CiteAckn.</th>
<th>HighView NoCite</th>
<th>HighView Cite</th>
<th>HighView CiteAckn.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comment at least 1 article</td>
<td>0.331 (0.471)</td>
<td>0.314 (0.465)</td>
<td>0.335 (0.473)</td>
<td>0.363 (0.482)</td>
<td>0.316 (0.466)</td>
<td>0.376 (0.485)</td>
</tr>
<tr>
<td>Number of articles commented</td>
<td>0.884 (1.658)</td>
<td>0.783 (1.492)</td>
<td>0.708 (1.295)</td>
<td>0.843 (1.451)</td>
<td>0.665 (1.263)</td>
<td>0.849 (1.432)</td>
</tr>
<tr>
<td>Average word count</td>
<td>44 (177)</td>
<td>41 (160)</td>
<td>65 (219)</td>
<td>96 (600)</td>
<td>43 (131)</td>
<td>60 (160)</td>
</tr>
<tr>
<td>Observations</td>
<td>242</td>
<td>258</td>
<td>257</td>
<td>223</td>
<td>275</td>
<td>258</td>
</tr>
</tbody>
</table>
Example 1: Traveler’s Dilemma

Original:
“When the game is played experimentally, most participants select a value close to $100.”
Example 1: Traveler’s Dilemma

- **Original:**
  “When the game is played experimentally, most participants select a value close to $100.”

- **Proposed change:**
  “When the game is played experimentally, most participants select a value higher than the Nash equilibrium and closer to $100. More precisely, the Nash equilibrium strategy solution proved to be a bad predictor of people’s behaviour in a TD with small bonus/malus and a rather good predictor if the bonus/malus parameter was big.”
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- **Expert:** Piergiuseppe Morone, Professor of Economic Policy at University of Rome
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▶ Expert: Piergiuseppe Morone, Professor of Economic Policy at University of Rome

▶ Expertise inferred from this paper:
Example 2: Repeated Game

- Article
  https://en.wikipedia.org/wiki/Repeated_game
- Talk Page
  https://en.wikipedia.org/wiki/Talk:Repeated_game
- Consent obtained from Oleg Korenok and Karl Schlag
Cosine similarity

- Cosine similarity of two documents measure the similarity between them in terms of overlapping vocabulary
  1. Doc 1: Expert's abstract, a
  2. Doc 2: Wikipedia article, b
Cosine similarity

- Cosine similarity of two documents measure the similarity between them in terms of overlapping vocabulary
  1. Doc 1: Expert's abstract, $a$
  2. Doc 2: Wikipedia article, $b$

- Construct two vectors, $A$ and $B$
  - enter both text files into a tokenizer, which divides text into a sequence of tokens, which roughly correspond to “words”
  - results processed by a stemmer, which reduces inflected or derived words to their word stem, base or root form
  - results passed to a tf-idf vectorizer (term frequency–inverse document frequency)
Cosine similarity

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- Calculate **cosine similarity** between \( A \) and \( B \):

  \[
  \cos(\theta) = \frac{A^T \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}
  \]
### Contribution quantity: Compound Poisson Linear Model

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>log(Word Count)</th>
<th>Coefficients</th>
<th>Standard Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>HighView</td>
<td>0.165</td>
<td>0.109</td>
<td>0.068</td>
</tr>
<tr>
<td></td>
<td>(0.275)</td>
<td>(0.282)</td>
<td>(0.281)</td>
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<td>(0.275)</td>
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<tr>
<td>Cosine Similarity</td>
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<td>log(Page Length)</td>
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<td>-0.017</td>
<td></td>
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<tr>
<td></td>
<td>(0.079)</td>
<td>(0.080)</td>
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<tr>
<td>Author Abstract View</td>
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<tr>
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<tr>
<td></td>
<td>(0.156)</td>
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<tr>
<td>Behavioral &amp; Experimental Econ.</td>
<td><em>0.619</em>*</td>
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<tr>
<td><strong>N</strong></td>
<td>8,825</td>
<td>8,659</td>
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</table>
Contribution quantity

- **Cosine similarity**: The more similar an article is to an expert’s published abstract, the longer the corresponding comment is. More specifically, a one-unit increase in cosine similarity leads to 9 times increase in the length of the expert’s comments.

- **Social distance**: Behavioral and experimental economists contribute 16% more than experts in other fields.

- **Cosine similarity** has a similar significant effect on overall contribution quality.
Contribution quality

- Each comment independently rated by 3 trained coders
  - Doctoral students in Information Economics
  - Masters students in Economics and Information Economics
  - Junior and senior undergraduate economics majors
- Assignment based on courses taken
- Use median rating for analysis
- Distribution of median “overall quality”
## Quality of comments: Self citation (logit)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Self-citation</th>
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<tbody>
<tr>
<td>HighView</td>
<td>0.008 0.019 0.014</td>
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<tr>
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<td>(0.059) (0.062) (0.060)</td>
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<tr>
<td>Citation</td>
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<td>(0.057) (0.058) (0.058)</td>
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<tr>
<td>Acknowledgement</td>
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<td>(0.060) (0.061) (0.062)</td>
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<tr>
<td>Cosine Similarity</td>
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<td>(0.186) (0.186)</td>
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<td>log(Page Length)</td>
<td>-0.012-0.017</td>
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<td>(0.031) (0.031)</td>
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<tr>
<td>Author Abstract View</td>
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<tr>
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<td>(0.462)</td>
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<tr>
<td>English Affiliation</td>
<td>0.057*</td>
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<td>(0.156)</td>
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<td>Behavioral &amp; Experimental Econ.</td>
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<td>(0.049)</td>
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<td>HighView×HighView×Acknowledgement</td>
<td>-0.187*** -0.207*** -0.206***</td>
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<tr>
<td></td>
<td>(0.052) (0.052) (0.253)</td>
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<tr>
<td>Acknowledgement×HighView×Acknowledgement</td>
<td>-0.102** -0.130** -0.118**</td>
</tr>
<tr>
<td></td>
<td>(0.051) (0.053) (0.052)</td>
</tr>
</tbody>
</table>

- Compared to AvgView-Acknowledgement, HighView-Acknowledgement discourages self-citation.
Motivation
Literature Review
Experimental Design
Results
**Conclusion**
Concluding Remarks

- Eliciting interests from experts
  - Citation benefit at High View increases participation;
  - Public acknowledgement at High View decreases negative response.
  - Longer social distance and higher reputation decrease participation

- Eliciting contribution quantity
  - Similarity of an article to an expert’s publication encourages contribution from experts

- Eliciting high quality
  - Acknowledgement elicits higher quality comments.

Lessons learned:
- Ask; Who asks - social distance;
- What do you ask: recommender system and expertise matching

Generalizable to other expert communities? arXiv
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