Quantifying Voter Biases in Online Platforms: An Instrumental Variable Approach

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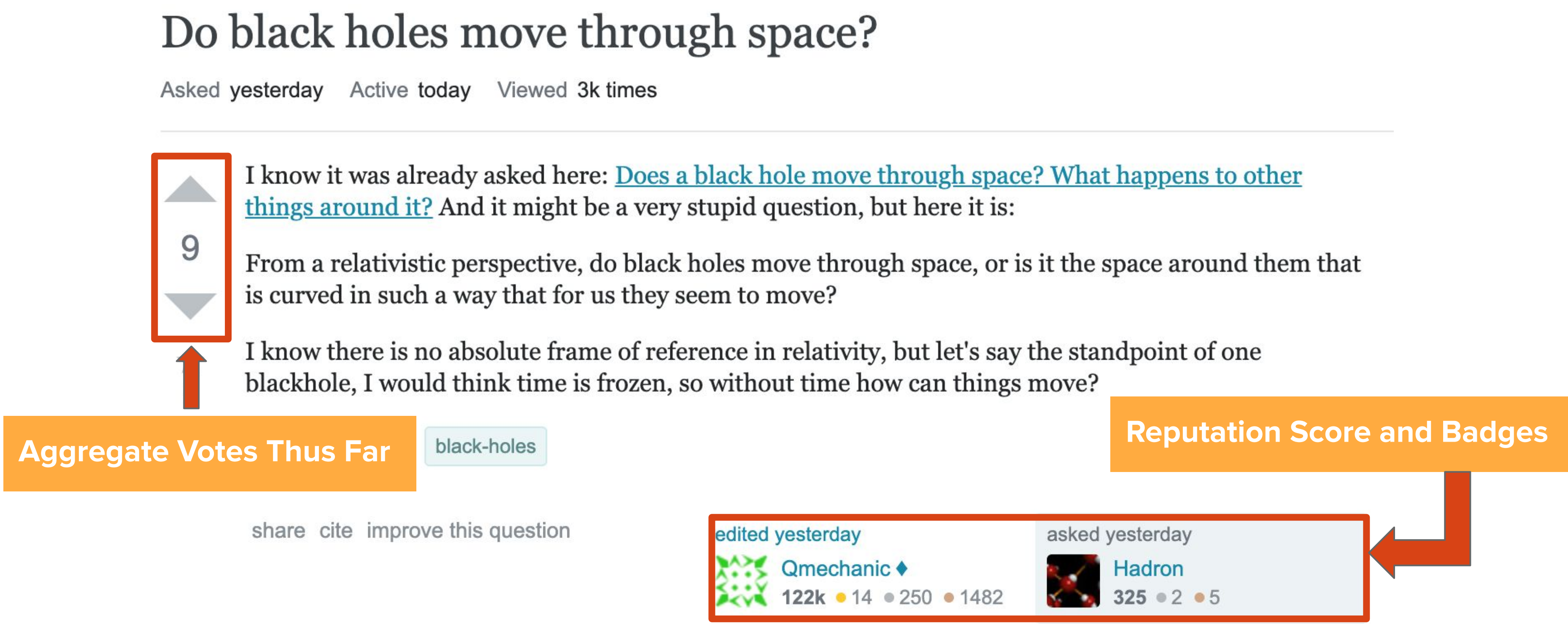
Question



Do black holes move through space?
Asked yesterday Active today Viewed 3k times
9
I know it was already asked here: Does a black hole move through space? What happens to other things around it? And it might be a very stupid question, but here it is:
From a relativistic perspective, do black holes move through space, or is it the space around them that is curved in such a way that for us they seem to move?
I know there is no absolute frame of reference in relativity, but let's say the standpoint of one blackhole, I would think time is frozen, so without time how can things move?
Aggregate Votes Thus Far
black-holes
Reputation Score and Badges
share cite improve this question
edited yesterday
Qmechanic ♦
122k ● 14 ● 250 ● 1482
asked yesterday
Hadron
325 ● 2 ● 5

Which answer would you vote?

Do black holes move through spaces?

24

Yes, they can move through space. LIGO has detected gravitational waves from multiple pairs of black holes orbiting each other, spiraling together, and merging.

share cite improve this answer edited yesterday answered yesterday

add a comment

13

Consider a black hole with lots of stuff in orbit around it. For example, most galaxies are like this (they have a big black hole at the centre, or, at least, there are good reasons to think that this is so). When all the orbiting stuff moves along together (while still orbiting), surely it makes sense to say the black hole is itself moving along too. For example, eventually one galaxy could bump into another. Indeed, this has happened many times, and with a big telescope we can see some such mergers ongoing now (or rather, at the moment the light set off towards our telescope).

share cite improve this answer answered 23 h

4

Yes. Here is a geometric perspective.

Take e.g. the Schwarzschild metric in coordinates $x^\mu = (t, r, \phi, \theta)$:

$$g_{\mu\nu}dx^\mu dx^\nu = -(1 - r_S/r)dt^2 + (1 - r_S/r)^{-1}dr^2 + r^2(d\theta^2 + \sin^2\theta d\phi^2) \quad \text{(Schwarzschild)}$$

where r_S is the Schwarzschild radius. The geometry as $r \to +\infty$ will look like Minkowski space in spherical coordinates (for the spacelike part):

$$g_{\mu\nu}dx^\mu dx^\nu = -dt^2 + dr^2 + r^2(d\theta^2 + \sin^2\theta d\phi^2) \qquad \text{(Minkowski)}\,.$$

Consider changing to Cartesian coordinates $(r, \phi, \theta) \to (x, y, z)$, doing a boost (say along the x direction), and changing back to spherical coordinates. The Minkowski geometry will look exactly the same.

However, doing the same for the Schwarzschild geometry will give you a different geometry! (Which I will not write down...) The new geometry corresponds to a boosted Schwarzschild black hole, one which moves at constant velocity relative to the distant observer at $r \to \infty$.

In fact, the same argument tells you that any *asymptotically flat* black hole can move relative to an observer far away from the black hole. (Of course they don't all have to move at constant speeds; it's just that one can construct constantly moving black hole geometries from the immobile ones by the above argument without actually calculating anything.)

Do black holes move through spaces?

Whose answer would you vote?

Yes, they can move through space. LIGO has detected gravitational waves from multiple pairs of black holes orbiting each other, spiraling together, and merging.

share cite improve this answer edited y

G. Smith
31.7k ● 3 ● 51 ● 97

add a comment

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share cite improve this answer

Andrew Steane
14.8k ● 1 ● 19 ● 72

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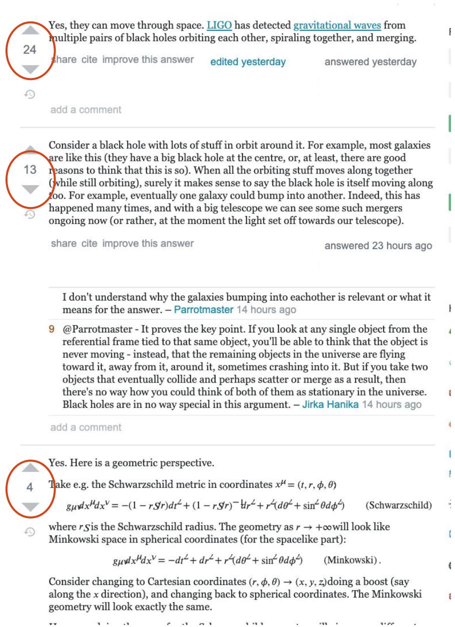
just that one can construct
above argument without a

share cite improve this answ

alexarvanitakis
1,177 ● 5 ● 13

Voter Bias

- **Reputation Bias**
  - inferring content quality in terms of user reputation
  - user with a higher reputation will receive more upvotes
- **Social Influence Bias**
  - decision is influenced by the prior decision of peers
  - the content with higher aggregate vote will receive more upvotes
- **Position Bias**
  - present content using a list-style format : Reddit, Stack Exchange
  - Content at the higher position will receive more votes



Related Work

- Voting Behavior
  - Users do not make independent voting decisions
  - Context ➔ Decision to vote, Polarity of vote [6] -- Sipos et al.
- Reputation Bias
  - Past reputation may be useful in predicting current success[7]
  - Reddit: user with higher comment karma tend to have higher ratings -- Liang et al.
- Social Influence Bias
  - Randomized Experiment: simulation via Amazon Mechanical Turk (AMT)
  - Observation Study
    - Statistical models for quantifying social influence bias:
      - Poisson regression[5]
      - Logistic regression[6]
      - etc.
- Position Bias
  - Abeliuk et al. [1] showed that the unpredictability of voting outcome is a consequence of the ordering policy.

Issue

- Reputation Bias
  - Only show the evidence of reputation bias, they do not provide any bias quantification
- Social Influence Bias
  - Randomized experiments: ethical issues, cost→ unfeasible
  - Observation Study:
    - Lack causal validation
    - Measure only the magnitude of association, rather than the **magnitude and direction of causation**
- Social Influence Bias VS. Position Bias
  - In many platforms, the presentation order of content depends on the aggregate user feedback. (Quora, StackOverflow.etc)
  - Hard for researchers to estimate the causal effects of social influence signal and position signal.

Why Stack Exchange?

- Complete
- Same governing rules for all sites
- Get to a correct answer v.s invoke a discussion

Table 2. Descriptive statistics for the selected Stack Exchange sites.

Site	Category	# Users	# Questions	# Answers
English	Culture	169,037	87,679	210,338
Superuser	Technology	547,175	356,866	529,214
Math	Science	356,699	822,059	1,160,697

StackExchange

Why English, Superuser, Math sites?

- High Coverage: culture [English], technology[Superuser], and science [Math].
- Large sites in their category according to #answers
- Vary in susceptibility to voter biases

Variable

Variables falls into 4 groups

- Site
  - The Stack Exchange site
- Question
  - the question that has been referred by the answer
- Answer
  - The answer in consideration
- Answerer
  - The user who created the answer

ID	Variable	Description
V_{1}	Site	The Stack Exchange site in consideration
V_{2}	T	The limiting time of bias formation specific to the question
V_{3}	QuestionViewCount	Number of users who viewed the question
V_{4}	QuestionFavoriteCount	Number of users who favorited the question
V_{5}	QuestionScore	Aggregate vote (total upvotes - total downvotes) on the question
V_{6}	QuestionScoreT-	Aggregate vote on the question before time T
V_{7}	QuestionScoreT+	Aggregate vote on the question after time T
V_{8}	QuestionCommentCount	Number of comments on the question
V_{9}	QuestionCommentCountT-	Number of comments on the question before time T
V_{10}	QuestionCommentCountT+	Number of comments on the question after time T
V_{11}	QuestionAnswerCount	Number of answers to the question
V_{12}	QuestionAnswerCountT-	Number of answers to the question before time T
V_{13}	QuestionAnswerCountT+	Number of answers to the question after time T
V_{14}	AnswerDayOfWeek	The day of answer creation
V_{15}	AnswerTimeOfDay	The time of answer creation
V_{16}	AnswerEpoch	Time gap between between the 1st post in site and the answer
V_{17}	AnswerTimeliness	Time gap between the question and the answer
V_{18}	AnswerOrder	Chronological order of the answer
V_{19}	AnswerScore	Aggregate vote on the answer
V_{20}	AnswerScoreT-	Aggregate vote on the answer before time T
V_{21}	AnswerScoreT+	Aggregate vote on the answer after time T
V_{22}	AnswerPosition	Position of the answer based on the aggregate vote
V_{23}	AnswerPositionT-	Position of the answer based on the aggregate vote before time T
V_{24}	AnswerPositionT+	Position of the answer based on the aggregate vote after time T
V_{25}	AnswerCommentCount	Number of comments on the answer
V_{26}	AnswerCommentCountT-	Number of comments on the answer before time T
V_{27}	AnswerCommentCountT+	Number of comments on the answer after time T
V_{28}	AnswererPostCount	Number of posts (questions and answers) written by the answerer
V_{29}	AnswererAnswerCount	Number of answers written by the answerer
V_{30}	AnswererActiveAge	Time gap between between the answerer's 1st post and the answer
V_{31}	AnswererReputation	Total score of questions and answers written by the answerer
V_{32}	AnswererReputationViaAnswer	Total score of answers written by the answerer
V_{33}	AnswererGoldCount	Number of gold badges acquired by the answerer
V_{34}	AnswererSilverCount	Number of silver badges acquired by the answerer
V_{35}	AnswererBronzeCount	Number of bronze badges acquired by the answerer
V_{36}	AnswererBadgeDistrribution	[AnswererGoldCount, AnswererSilverCount, AnswererBronzeCount]
V_{37}	AnsweredQuestionViewTotal	Total number of users who viewed past questions answered by the answerer
V_{38}	AnsweredQuestionFavoriteTotal	Total number of users who favorited past questions answered by the answerer
V_{39}	AnsweredQuestionScoreTotal	Total score of past questions answered by the answerer
V_{40}	AnsweredQuestionCommentTotal	Total number of comments on past questions answered by the answerer
V_{41}	AnsweredQuestionAnswerTotal	Total number of answers to past questions answered by the answerer

Method Overview

- **Goal: Quantify the degree of voter bias in online platform.**

    - **To determine bias, we need to estimate causal effects of different impression signals on observed votes.**

- **Methodology - Ordinary Least Square(OLS) VS Instrumental Variable(IV)**

OLS:

- Captures correlations among variables, non-causal

IV:

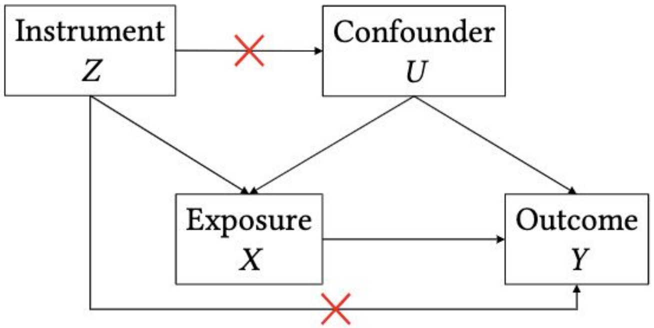
- Reason underlying causal structure

Limitation of OLS:

- Neglect the effect of hidden cofounder.
- E.g. Education → Earning
  Hidden confounder: the unobserved ability of individual
  Affect both education level and earning

Why Instrumental Variable Model?

- **Existence of hidden confounder prevents standard regression method from causal effect**
- **Identify candidate instruments correlate only with independent variable**
- **Eliminate instrument that could affect hidden cofounder**
- **Estimating causal effect in the presence of hidden confounder**



Example: the causal effect of education on earnings

- Confounder - the unobserved ability of individuals
- Exposure - level of education that an individual attains
- Outcome - the wage he/she receives
- Instrument - proximity to college (variables which affect education but do not affect earnings either directly or indirectly)

Instrumental variable Estimation

Instrument Z- A variable to eliminate the effects of confounders

- **Relevance condition**: Z is correlated with the exposure X
- **Exclusion restriction:** Z does not affect outcome directly, except through exposure X
- **Marginal Exchangeability**: instrument Z and outcome don't share cause

Aim: identify instrument that has a strong correlation with impression signal(exposure).

The parallels between voter bias quantification and instrumental variable method

IV Terminology	Bias Terminology	Example
Outcome	Aggregate Feedback	Mean of votes on content
Exposure	Impression Signal	Reputation of the contributing user
Confounder	Unobserved Quality	What a voter assesses the quality of the content to be
Regression Coefficient	Voter Bias	How the reputation of the contributing user affects the mean vote

IV model for Reputation Bias

Outcome: Aggregate vote of the answer

Exposure: Reputation of answer, based on the reputation and badge system on stackExchange.

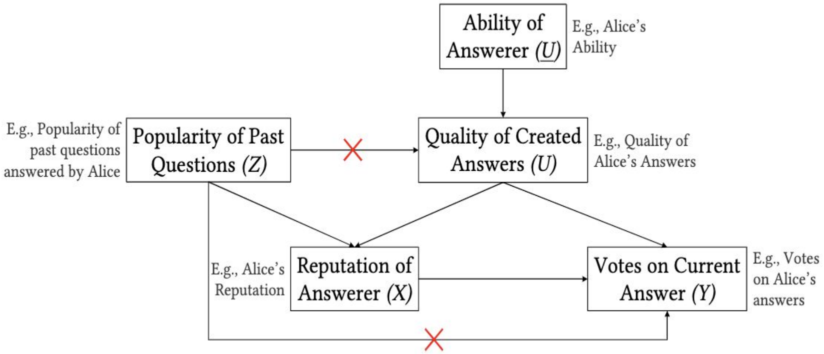
Variables:
AnswererReputation
AnswererReputationViaAnswer
AnswererGoldCount
AnswererSilverCount
AnswererBronzeCount

Assumption: all voters observe same state of reputation

IV model for Reputation Bias

Instrument:

Answerer's activity --- violate marginal exchangeability



Popularity of past questions responded by the answerer

Instrument Variables:

AnsweredQuestionViewTotal,
AnsweredQuestionFavoriteTotal,
AnsweredQuestionScoreTotal,
AnsweredQuestionCommentTotal,
AnsweredQuestionAnswerTotal

Control: Site,
QuestionViewCount,
QuestionFavoriteCount,
QuestionScore,
QuestionCommentCoun,
QuestionAnswerCount

Confounder:

Ability of Answerer

Joint IV Model for Social Influence Bias and Position Bias

Why Joint Model?

The presentation order of answers at Stack Exchange is the aggregate vote so far. Two signal vary together. Hard to isolate.

Estimate the causal effects of initial votes and resultant position on subsequent votes

Joint IV Model for Social Influence Bias and Position Bias

Outcome: aggregate vote on the answer after an initial bias formation period.

Exposure: initial votes and resultant position of answer.

(1). AnswerScoreT-⟨V20⟩ - captures the aggregate vote on answer based on the votes before time T;

(2). AnswerPositionT-⟨V23⟩ - captures the position of answer based on the aggregate vote before time T.

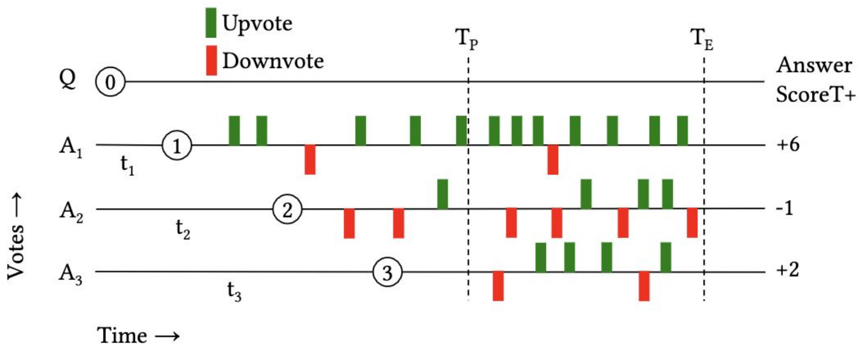
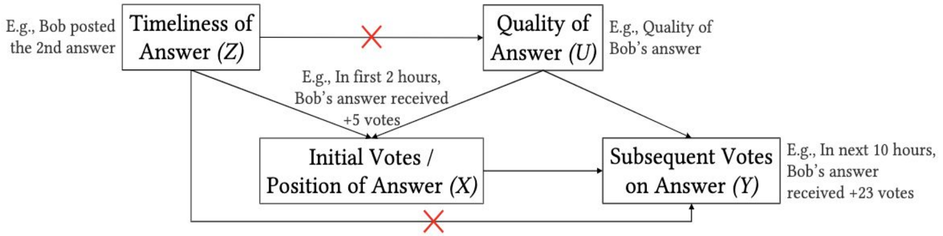


illustration of Bias information period

Joint IV Model for Social Influence Bias and Position Bias



Instrument:

activities on the question within the bias formation period

actual time of answer

relative timeliness of answer

Variable: AnswerTimeliness, AnswerOrder

Control: Site, AnswererReputationViaAnswer

Result

Two-Stage Least Squares (2SLS) Method VS OLS at English, Math, and Superuser

Quantifying reputation bias

Causal Effect of Reputation Score: the causal effect of reputation score on the aggregate vote is small

Causal Effect of Badges: high effect for gold badges, a moderate effect for silver badges, and low effect for bronze badges

Two-Stage Least Squares (2SLS) :

- First stage: regress each exposure variable on all instrumental and control variables in the model and obtain the predicted values from the regressions.
- Second stage, regress the outcome variable on the predicted exposures from the first stage, along with the control variables.

Table 5. Causal effects (regression coefficients) of answerer's reputation score and badges on the aggregate vote in English. All results presented in this table are statistically significant—validated via two-tailed t-tests—with $p < 0.001$. The results suggest that OLS and IV provide similar estimates for reputation score, whereas they differ a lot in estimating the effects of badges. Notably, *OLS tends to assign equal weights to all badges, whereas IV assigns more weights to gold badges.*

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩			
	(*for estimating the effect of Exposure*)	X = AnswererReputation ⟨V_{31}⟩		X = AnswererReputationViaAnswer ⟨V_{32}⟩	
Site	$Z + C$	OLS	IV	OLS	IV
English	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.092 (± 0.001)	0.089 (± 0.001)	0.090 (± 0.002)	0.088 (± 0.002)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.101 (± 0.002)	0.098 (± 0.001)	0.099 (± 0.002)	0.097 (± 0.002)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.092 (± 0.001)	0.088 (± 0.002)	0.090 (± 0.002)	0.086 (± 0.001)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.101 (± 0.002)	0.093 (± 0.001)	0.099 (± 0.001)	0.092 (± 0.002)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.092 (± 0.001)	0.086 (± 0.002)	0.090 (± 0.002)	0.084 (± 0.001)
	V_{39} + QuestionScore ⟨V_5⟩	0.100 (± 0.001)	0.092 (± 0.001)	0.099 (± 0.002)	0.090 (± 0.001)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.092 (± 0.001)	0.070 (± 0.002)	0.090 (± 0.002)	0.068 (± 0.001)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.093 (± 0.001)	0.070 (± 0.001)	0.091 (± 0.002)	0.069 (± 0.002)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.092 (± 0.001)	0.076 (± 0.001)	0.090 (± 0.002)	0.075 (± 0.002)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.100 (± 0.001)	0.084 (± 0.001)	0.098 (± 0.001)	0.083 (± 0.002)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.092 (± 0.001)	0.081 (± 0.001)	0.090 (± 0.002)	0.079 (± 0.002)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.098 (± 0.002)	0.087 (± 0.001)	0.096 (± 0.001)	0.085 (± 0.001)

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩					
	(*for estimating the effect of Exposure*)	X = AnswererGoldCount ⟨V_{33}⟩		X = AnswererSilverCount ⟨V_{34}⟩		X = AnswererBronzeCount ⟨V_{35}⟩	
Site	$Z + C$	OLS	IV	OLS	IV	OLS	IV
English	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.184 (± 0.006)	0.712 (± 0.014)	0.138 (± 0.003)	0.225 (± 0.004)	0.157 (± 0.003)	0.178 (± 0.003)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.219 (± 0.005)	0.794 (± 0.014)	0.158 (± 0.003)	0.250 (± 0.004)	0.183 (± 0.002)	0.198 (± 0.003)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.184 (± 0.006)	0.543 (± 0.009)	0.138 (± 0.003)	0.187 (± 0.003)	0.157 (± 0.003)	0.175 (± 0.003)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.206 (± 0.006)	0.579 (± 0.010)	0.153 (± 0.002)	0.200 (± 0.003)	0.176 (± 0.003)	0.186 (± 0.003)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.184 (± 0.006)	0.570 (± 0.010)	0.138 (± 0.003)	0.192 (± 0.003)	0.157 (± 0.003)	0.170 (± 0.003)
	V_{39} + QusestionScore ⟨V_5⟩	0.199 (± 0.005)	0.613 (± 0.010)	0.151 (± 0.003)	0.207 (± 0.003)	0.177 (± 0.003)	0.183 (± 0.003)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.184 (± 0.006)	0.447 (± 0.010)	0.138 (± 0.003)	0.153 (± 0.003)	0.157 (± 0.003)	0.135 (± 0.003)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.183 (± 0.006)	0.448 (± 0.010)	0.138 (± 0.003)	0.154 (± 0.004)	0.157 (± 0.002)	0.136 (± 0.003)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.184 (± 0.006)	0.500 (± 0.011)	0.138 (± 0.003)	0.170 (± 0.003)	0.157 (± 0.003)	0.149 (± 0.003)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.201 (± 0.006)	0.551 (± 0.010)	0.150 (± 0.003)	0.188 (± 0.004)	0.173 (± 0.003)	0.165 (± 0.003)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.184 (± 0.006)	0.338 (± 0.009)	0.138 (± 0.003)	0.143 (± 0.003)	0.157 (± 0.003)	0.145 (± 0.003)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.195 (± 0.005)	0.382 (± 0.008)	0.149 (± 0.003)	0.157 (± 0.003)	0.176 (± 0.003)	0.167 (± 0.003)

Table 6. Causal effects (regression coefficients) of answerer's reputation score and badges on the aggregate vote in Math. All results presented in this table are statistically significant—validated via two-tailed t-tests—with $p < 0.001$. The results suggest that OLS and IV provide similar estimates for reputation score, whereas they differ a lot in estimating the effects of badges. Notably, *OLS tends to assign equal weights to all badges, whereas IV assigns more weights to gold badges.*

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩			
	(*for estimating the effect of Exposure*)	X = AnswererReputation ⟨V_{31}⟩		X = AnswererReputationViaAnswer ⟨V_{32}⟩	
Site	$Z + C$	OLS	IV	OLS	IV
Math	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.056 (± 0.001)	0.055 (± 0.001)	0.053 (± 0.001)	0.051 (± 0.001)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.067 (± 0.001)	0.061 (± 0.001)	0.063 (± 0.001)	0.057 (± 0.001)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.056 (± 0.001)	0.057 (± 0.001)	0.053 (± 0.001)	0.053 (± 0.001)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.061 (± 0.001)	0.057 (± 0.001)	0.058 (± 0.001)	0.053 (± 0.001)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.056 (± 0.001)	0.055 (± 0.001)	0.053 (± 0.001)	0.051 (± 0.001)
	V_{39} + QuestionScore ⟨V_5⟩	0.058 (± 0.001)	0.053 (± 0.001)	0.055 (± 0.001)	0.049 (± 0.001)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.056 (± 0.001)	0.040 (± 0.001)	0.053 (± 0.001)	0.037 (± 0.001)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.057 (± 0.001)	0.041 (± 0.001)	0.054 (± 0.001)	0.038 (± 0.001)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.056 (± 0.001)	0.040 (± 0.001)	0.053 (± 0.001)	0.037 (± 0.001)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.060 (± 0.001)	0.043 (± 0.001)	0.057 (± 0.001)	0.040 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.056 (± 0.001)	0.048 (± 0.001)	0.053 (± 0.001)	0.043 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.062 (± 0.001)	0.055 (± 0.001)	0.059 (± 0.001)	0.050 (± 0.001)

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩					
	(*for estimating the effect of Exposure*)	X = AnswererGoldCount ⟨V_{33}⟩		X = AnswererSilverCount ⟨V_{34}⟩		X = AnswererBronzeCount ⟨V_{35}⟩	
Site	$Z + C$	OLS	IV	OLS	IV	OLS	IV
Math	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.086 (± 0.001)	0.234 (± 0.002)	0.076 (± 0.001)	0.104 (± 0.001)	0.090 (± 0.001)	0.112 (± 0.001)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.122 (± 0.002)	0.262 (± 0.003)	0.094 (± 0.001)	0.116 (± 0.001)	0.117 (± 0.001)	0.125 (± 0.001)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.086 (± 0.001)	0.217 (± 0.002)	0.076 (± 0.001)	0.099 (± 0.001)	0.090 (± 0.001)	0.115 (± 0.001)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.105 (± 0.002)	0.218 (± 0.002)	0.083 (± 0.001)	0.099 (± 0.001)	0.103 (± 0.001)	0.115 (± 0.001)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.086 (± 0.001)	0.214 (± 0.002)	0.076 (± 0.001)	0.098 (± 0.001)	0.090 (± 0.001)	0.112 (± 0.001)
	V_{39} + QuestionScore ⟨V_5⟩	0.100 (± 0.001)	0.206 (± 0.002)	0.078 (± 0.001)	0.094 (± 0.001)	0.098 (± 0.001)	0.107 (± 0.001)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.086 (± 0.001)	0.154 (± 0.002)	0.076 (± 0.001)	0.072 (± 0.001)	0.090 (± 0.001)	0.081 (± 0.001)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.089 (± 0.002)	0.157 (± 0.002)	0.077 (± 0.001)	0.073 (± 0.001)	0.092 (± 0.001)	0.083 (± 0.001)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.086 (± 0.001)	0.153 (± 0.002)	0.076 (± 0.001)	0.072 (± 0.001)	0.090 (± 0.001)	0.081 (± 0.001)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.094 (± 0.001)	0.165 (± 0.002)	0.081 (± 0.001)	0.077 (± 0.001)	0.098 (± 0.001)	0.087 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.086 (± 0.001)	0.133 (± 0.002)	0.076 (± 0.001)	0.079 (± 0.001)	0.090 (± 0.001)	0.092 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.113 (± 0.002)	0.179 (± 0.002)	0.085 (± 0.001)	0.090 (± 0.001)	0.108 (± 0.001)	0.110 (± 0.001)

Table 7. Causal effects (regression coefficients) of answerer's reputation score and badges on the aggregate vote in Superuser. All results presented in this table are statistically significant—validated via two-tailed t-tests—with $p < 0.001$. The results suggest that OLS and IV provide similar estimates for reputation score, whereas they differ a lot in estimating the effects of badges. Notably, *OLS tends to assign equal weights to all badges, whereas IV assigns more weights to gold badges.*

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩			
	(*for estimating the effect of Exposure*)	X = AnswererReputation ⟨V_{31}⟩		X = AnswererReputationViaAnswer ⟨V_{32}⟩	
Site	$Z + C$	OLS	IV	OLS	IV
Superuser	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.054 (± 0.001)	0.045 (± 0.001)	0.052 (± 0.001)	0.043 (± 0.001)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.067 (± 0.001)	0.062 (± 0.001)	0.065 (± 0.001)	0.060 (± 0.001)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.054 (± 0.001)	0.054 (± 0.001)	0.052 (± 0.001)	0.052 (± 0.001)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.065 (± 0.001)	0.062 (± 0.001)	0.063 (± 0.001)	0.060 (± 0.001)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.054 (± 0.001)	0.052 (± 0.001)	0.052 (± 0.001)	0.050 (± 0.001)
	V_{39} + QusestionScore ⟨V_5⟩	0.065 (± 0.001)	0.061 (± 0.001)	0.064 (± 0.001)	0.059 (± 0.001)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.054 (± 0.001)	0.038 (± 0.001)	0.052 (± 0.001)	0.036 (± 0.001)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.054 (± 0.001)	0.038 (± 0.001)	0.052 (± 0.001)	0.036 (± 0.001)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.054 (± 0.001)	0.045 (± 0.001)	0.052 (± 0.001)	0.044 (± 0.001)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.062 (± 0.001)	0.053 (± 0.001)	0.060 (± 0.001)	0.052 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.054 (± 0.001)	0.048 (± 0.001)	0.052 (± 0.001)	0.046 (± 0.001)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.063 (± 0.001)	0.060 (± 0.001)	0.062 (± 0.001)	0.057 (± 0.001)

	Instrument and Control	Y = AnswerScore ⟨V_{19}⟩					
	(*for estimating the effect of Exposure*)	X = AnswererGoldCount ⟨V_{33}⟩		X = AnswererSilverCount ⟨V_{34}⟩		X = AnswererBronzeCount ⟨V_{35}⟩	
Site	$Z + C$	OLS	IV	OLS	IV	OLS	IV
Superuser	AnsweredQuestionViewTotal ⟨V_{37}⟩	0.106 (± 0.004)	0.414 (± 0.009)	0.081 (± 0.002)	0.139 (± 0.003)	0.082 (± 0.002)	0.097 (± 0.002)
	V_{37} + QuestionViewCount ⟨V_3⟩	0.175 (± 0.004)	0.591 (± 0.009)	0.116 (± 0.002)	0.196 (± 0.003)	0.123 (± 0.001)	0.137 (± 0.002)
	AnsweredQuestionFavoriteTotal ⟨V_{38}⟩	0.106 (± 0.004)	0.399 (± 0.007)	0.081 (± 0.002)	0.143 (± 0.002)	0.082 (± 0.002)	0.123 (± 0.002)
	V_{38} + QuestionFavoriteCount ⟨V_4⟩	0.147 (± 0.004)	0.459 (± 0.006)	0.103 (± 0.001)	0.165 (± 0.002)	0.110 (± 0.002)	0.142 (± 0.002)
	AnsweredQuestionScoreTotal ⟨V_{39}⟩	0.106 (± 0.004)	0.406 (± 0.007)	0.081 (± 0.002)	0.144 (± 0.005)	0.082 (± 0.002)	0.117 (± 0.002)
	V_{39} + QusestionScore ⟨V_5⟩	0.162 (± 0.003)	0.481 (± 0.006)	0.109 (± 0.001)	0.170 (± 0.002)	0.116 (± 0.002)	0.139 (± 0.002)
	AnsweredQuestionCommentTotal ⟨V_{40}⟩	0.106 (± 0.004)	0.266 (± 0.006)	0.081 (± 0.002)	0.099 (± 0.003)	0.082 (± 0.002)	0.082 (± 0.002)
	V_{40} + QuestionCommentCount ⟨V_8⟩	0.106 (± 0.004)	0.266 (± 0.007)	0.081 (± 0.002)	0.099 (± 0.003)	0.081 (± 0.001)	0.082 (± 0.002)
	AnsweredQuestionAnswerTotal ⟨V_{41}⟩	0.106 (± 0.004)	0.349 (± 0.007)	0.081 (± 0.002)	0.124 (± 0.002)	0.082 (± 0.002)	0.100 (± 0.002)
	V_{41} + QuestionAnswerCount ⟨V_{11}⟩	0.144 (± 0.003)	0.419 (± 0.007)	0.102 (± 0.002)	0.148 (± 0.002)	0.105 (± 0.002)	0.120 (± 0.002)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41}	0.106 (± 0.004)	0.244 (± 0.006)	0.081 (± 0.002)	0.110 (± 0.002)	0.082 (± 0.002)	0.093 (± 0.002)
	V_{37}, V_{38}, V_{39}, V_{40}, V_{41} + V_3, V_4, V_5, V_8, V_{11}	0.152 (± 0.003)	0.337 (± 0.005)	0.105 (± 0.002)	0.141 (± 0.002)	0.113 (± 0.002)	0.131 (± 0.002)

Result

Quantifying social influence and Position Bias

Causal Effect of Initial Vote: OLS assigns high weights to initial votes, 1.8–2.3xof IV weights (based on initial 5% votes)

Causal Effect of Initial Position: IV assigns high weights to initial position, at times 1.9xof OLS weights (based on initial 5%votes).

Effect of Bias Formation Period: increasing the bias formation period T leads to a decrease in causal effects for both initial votes and position

Table 8. The causal effects (IV estimates) of initial votes and position on subsequent votes in ENGLISH, SUPERUSER and MATH. All results presented in this table are statistically significant—validated via two-tailed t-tests—with $p < 0.001$. The results suggest that OLS and IV differ a lot in quantifying the effects of initial votes and position. Notably, *OLS underestimates reputation bias and overestimates social influence bias significantly.*

		Y = AnswerScoreT+ ⟨V_{21}⟩, Z_1 = AnswerTimeliness ⟨V_{17}⟩, Z_2 = AnswerOrder ⟨V_{18}⟩			
		X_1 = AnswerScoreT- ⟨V_{20}⟩		X_2 = AnswerPositionT- ⟨V_{23}⟩	
Site	T	OLS	IV	OLS	IV
English	$T_{0.05}$	0.803 (± 0.007)	0.442 (± 0.087)	0.215 (± 0.014)	0.401 (± 0.037)
	$T_{0.10}$	0.821 (± 0.006)	0.403 (± 0.080)	0.205 (± 0.012)	0.337 (± 0.030)
	$T_{0.15}$	0.819 (± 0.005)	0.385 (± 0.073)	0.184 (± 0.010)	0.300 (± 0.025)
	$T_{0.20}$	0.791 (± 0.005)	0.354 (± 0.067)	0.161 (± 0.009)	0.270 (± 0.022)
	$T_{0.25}$	0.752 (± 0.004)	0.323 (± 0.061)	0.126 (± 0.008)	0.230 (± 0.018)
	$T_{0.30}$	0.699 (± 0.004)	0.289 (± 0.057)	0.100 (± 0.008)	0.204 (± 0.016)
Math	$T_{0.05}$	0.802 (± 0.003)	0.359 (± 0.037)	0.470 (± 0.007)	0.483 (± 0.010)
	$T_{0.10}$	0.880 (± 0.003)	0.355 (± 0.036)	0.446 (± 0.005)	0.445 (± 0.009)
	$T_{0.15}$	0.920 (± 0.003)	0.352 (± 0.035)	0.380 (± 0.005)	0.399 (± 0.008)
	$T_{0.20}$	0.921 (± 0.003)	0.342 (± 0.034)	0.339 (± 0.004)	0.373 (± 0.007)
	$T_{0.25}$	0.885 (± 0.002)	0.331 (± 0.034)	0.284 (± 0.004)	0.343 (± 0.007)
	$T_{0.30}$	0.833 (± 0.002)	0.324 (± 0.033)	0.240 (± 0.003)	0.319 (± 0.006)
Superuser	$T_{0.05}$	1.814 (± 0.010)	0.800 (± 0.122)	0.842 (± 0.025)	1.209 (± 0.058)
	$T_{0.10}$	1.939 (± 0.008)	0.742 (± 0.108)	0.784 (± 0.021)	1.018 (± 0.045)
	$T_{0.15}$	1.983 (± 0.007)	0.689 (± 0.097)	0.705 (± 0.017)	0.899 (± 0.037)
	$T_{0.20}$	1.888 (± 0.005)	0.633 (± 0.087)	0.594 (± 0.014)	0.793 (± 0.030)
	$T_{0.25}$	1.633 (± 0.004)	0.583 (± 0.076)	0.463 (± 0.012)	0.712 (± 0.025)
	$T_{0.30}$	1.477 (± 0.003)	0.526 (± 0.067)	0.363 (± 0.009)	0.630 (± 0.021)

Implication for Online Voting Behavior

- How Community Type Affects Voting.
- On Social Prestige of Badges.

Implications for User Interface Design

- Conceal Impression Signals.
- Delay the Votes.
- Randomize Presentation Order.

Informing Policy Design

- De-biasing Votes.
- Community Dependent Policy Design.

Strength & Limitation

Strength:

- Flow is clear
- Detail explanation
- Clear reasoning
- Complete Coverage of Related Work
- Easy to understand

Limitation:

- “Inflexible” Assumptions
    - All voters arrive observe the same state
- External influence
    - Twitter Promotion, etc.
- Untestifiable assumptions
    - exclusion restriction
    - marginal exchangeability

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