The Social Influence of Political Crowds in News Evaluation

MAURICE JAKESCH[1,2], MORAN KOREN[3], ANNA EVTUSHENKO[1], MOR NAAMAN[1,2],
[1]Cornell University [2]Cornell Tech [3]Technion

Social influence plays a major role in politics and online social media. In this study, we examine how the perceived political makeup of a crowd affects the strength of social influence in political news evaluation. Are liberals easily persuaded by opinions coming from a liberal crowd, while resisting the influence of conservative crowds? We designed a large-scale experiment (N=1,000) to investigate how politically-annotated social signals affect participants' opinion formation. In times rife with misinformation and polarization, our findings are optimistic: social influence seems to be largely non-political. That is, liberals and conservatives were equally influenced by majority-Democrat and majority-Republican crowds when evaluating news claims. At the same time, we replicate the findings of earlier studies showing that people are inclined to discard content that is inconsistent with their political views. The observation that people have strong negative reactions to politically opposed content, but not to uncongenial social signals open avenues for the design of depolarizing social rating systems.

1 INTRODUCTION

Political polarization – the vast and growing disagreement on political values – has become a major concern in American politics and globally [8, 51]. Pew Research finds record levels of disagreement on questions of welfare, race, immigration and foreign policy in the U.S. in their 2017 report [16]. Increasingly negative attitudes towards out-party members [1, 32] may impair the functioning of democracy more broadly [2, 55].

There is a growing concern that social media sites could exacerbate political polarization [55]. The hypothesized underlying mechanism is differential exposure: the social clustering [19, 39, 57] that takes place when social networking sites help users connect with "people like them," as well as recommendation algorithms that curate content a particular user would like to see, may lead to "echo chambers" or "filter bubbles" [43] in which individuals are largely exposed to conforming views. While it is evident that conservatives and liberals do consume different information online [12, 28], there is an ongoing debate whether social networking sites indeed expose individuals to overly conforming content compared to offline interactions and traditional media [7, 9, 11].

In this short paper, we explore an alternative cause of group polarization on social media sites: *that social rating systems which aggregate opinions of political crowds may be polarizing in and of themselves.* In other words, people may be impacted differently by social signals based on their political views. Given the pervasiveness of indicators of aggregated opinions on social media sites [22], it is important to investigate whether they may lead to *polarized instead of wise crowds.*

We know that group opinions exert both normative and informative influence over individuals[4, 23]. In addition, we may have estimates of the ideological composition of the group that created a social signal. For example, we know that the upvotes in the "r/esist" subreddit are coming from a liberal crowd, whereas comments under a Breitbart article

Manuscript submitted to ACM

represent a primarily conservative opinion. This knowledge of group ideology can help better evaluate a signal's informativeness, but it may also interact with social influence in potentially polarizing ways:

(a) **Tribal influence:** Individuals might be overly influenced by social signals that come from their ideological group. A conservative may be moved by the upvotes in a conservative subreddit, but indifferent towards the ones she sees in a liberal subreddit. This hypothesis is supported by research suggesting that the effectiveness of social influence depends on identification [34] and perceived similarity [13, 52].
(b) **Selective influence:** Individuals may be overly influenced by social signals that affirm their pre-existing political views. A liberal may be influenced by a crowd supporting a Democrat-consistent claim, but ignore support for Republican-consistent claims[1]. This hypothesis is supported by research motivated reasoning [35, 56], showing that individuals tend to discard information that would lead to cognitive dissonance [24].
(c) **Rational Influence:** Individuals may be influenced more by informative signals. For example, a majority-Democrat crowd rejecting a Democrat-consistent claim is more informative than the rejection of the same claim by a majority-Republican crowd. This behavior corresponds to the learning process of a rational Bayesian agent in a politically polarized environment.

Establishing whether social influence and political bias interact is a crucial step in understanding and addressing issues of political polarization on social media websites. To isolate the effect of social influence from effects of network homophily [50], we designed a large-scale experiment (N=1,000) where we test how the makeup of political crowds affects opinion formation. Specifically, we evaluate how politically-annotated social signals change whether participants believed a political news claim was true. We find that participants – as expected – tended to discard claims that did not align with their political views. However, they are reliably influenced by social signals independently of the political composition of the crowd providing these signals. We find no evidence of selective influence for either both liberals and conservative, and weak evidence for *tribal-rational* influence among liberals, who were more likely to change their evaluation when an informative signal came from a majority-Democrat crowd. Generally speaking, our results imply that the mechanism underlying social rating systems is less political than broadly believed.

We discuss how the finding that counter-attitudinal content, but not a social signal from an uncongenial crowd, evokes negative reactions opens avenues for the design of depolarizing social rating systems.

2 BACKGROUND

Our work connects three areas of prior research that we briefly touch on for this short paper: social influence, political bias, and rating systems.

Asch's conformity experiments [4, 14] in the 1950s initiated an extensive field of research on social influence and group conformity [38]. People's opinions are affected by those of their peers, as groups exert normative pressure and are a source information[23]. Most related to our study, researchers have found that similarity increases the strength of social influence [13, 34, 52] and that partisan groups may sustain themselves through social influence [25]. Pronin et al. have shown that in political debates, peer social influence may affect opinions more than policies' actual content [46]. In cases where opinions are not well-formed, observing the choice of another person creates *social defaults* [31]. It must be noted that it is notoriously hard to separate social influence from homophily in real-world settings [50].

Researchers have also extensively studied biases in political thinking. We know that biased cognitive processes affect the way people process information through *motivated reasoning* [35]: individuals have various cognitive strategies to

[1]The paper is written in the context of the U.S political system, using left/liberal and right/conservative labels

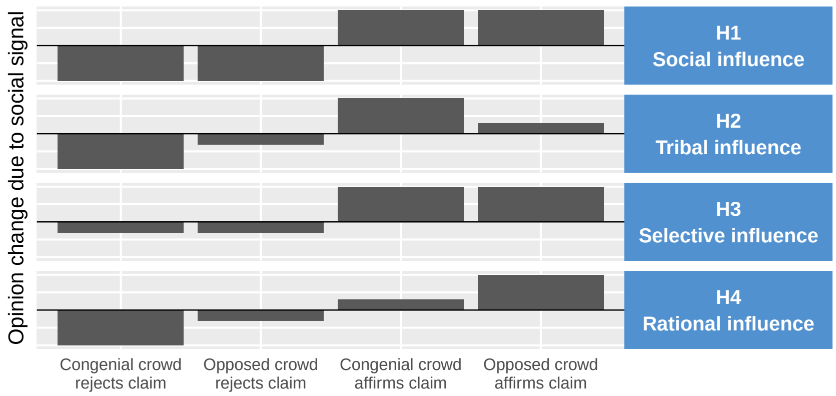

Fig. 1. Hypotheses over how a social signal may affect participants' opinions of a *politically aligned* claim.

be skeptical of information that may falsify their firmly held beliefs. Motivated reasoning is associated with attitude polarization [53, 56], especially for those with high levels of political sophistication [26]. For example, both liberals and conservatives believe the economy is improving when their party is in power, vice versa [10]. Individuals may avoid incongruent information in the first place due to the discomfort of *cognitive dissonance* [24]. Various studies have found that exposing individuals to politically misaligned views may even backfire [5, 42, 58]. This is particularly relevant in online environments where individuals have many different viewpoints to choose from [12, 28], and the tendency to stick with conforming content may be exacerbated through personalized content curation [43].

Researchers have explored the role of social rating systems on opinion formation. The "digitization of word of mouth" is a pervasive feature of websites [22]. It affects users' opinions [21] and shapes the diffusion of user-generated content [6] in complex ways [47]. The fact that the feedback of the earlier users' votes affects the behavior of those that follow [40] creates system dynamics with unpredictable and unequal outcomes [48]. Some of these dynamics may be explained through models of information cascades [3], although a signal-following heuristic may better explain behaviors than rational Bayesian updating [30]. Most related to our study, Deri et al. find that individuals may take arbitrary political sides on an issue based on the votes and political association of the first few users [36].

3 METHODS

We designed and executed an online experiment to quantify the effect of exposure to the aggregated opinion of a politically-annotated crowd on participants' opinion of political news claims. We randomly assigned users to either a control group where they saw no social signal, or one of two treatment groups where they saw social signals from majority-Democrat or majority-Republican crowds. We showed participants different political news claims and asked them to tell us whether they thought they were true or false.

3.1 Hypotheses and preregistration

We formalize our research questions into a set of empirically testable hypotheses, drawing on types of influence mentioned in the introduction:

(H0) No influence: compared to a control condition, news evaluations do not change significantly when participants see a social rating.

(H1) Social influence: participants change their evaluations independently of the politics of the crowd or the news claim.
(H2) Tribal influence: participants change their evaluations more for if they politically identify with the crowd.
(H3) Selective influence: participants change their evaluations more if the social signal supports their pre-existing political views.
(H4) Rational influence: participants change their evaluations more for informative signals when the social signal supports a claim that does not align with the crowd's politics.

An illustration of the hypothesized effects for a *politically aligned* claim is shown in Figure 1. For example, the second row of the figure shows that participants would change their evaluations when seeing signals from a congenial crowd, but not from an opposed crowd. We test these hypotheses separately for liberal and conservative participants. As the hypotheses are orthogonal, we should be able to estimate their relative effects through a linear model. We preregistered the full study, the analysis and hypotheses (with the exception of H3), available at http://aspredicted.org/blind.php?x=hx82az.

3.2 Experimental design

Our experiment imitated three typical elements of people's online experience: a news claim rendered as a news headline without the actual article (element 1 in Figure 2); the aggregated opinion of prior users who have seen and rated the claim (element 3); and buttons to rate the claim as either *true* or *false*, similar to the *upvote* or *like* features on social media platforms (4). In addition, we displayed the political composition of the users who supposedly rated the headline prior to the participant (2). We varied both the politics of the headline (1) and the social signal (3) as part of our experimental manipulation. The composition of the crowd (2) was explained to the participant before the start of the study and did not change within-subject. The different elements appeared successively so that participants spent some time focusing on each.

We used a 2x3x2 mixed factorial design:

(1) *Headline politics (within-subjects)*: Each participant rated 16 headlines. Four of these headlines were Democrat-consistent and four were Republican-consistent. The remaining eight claims were non-political decoy headlines designed to disguise the purpose of the study.
(2) *Crowd makeup treatment (between-subjects)*: Participants were randomly assigned to either the control, the majority-Democrat or the majority-Republican group. While participants in the control group saw no social signal, participants in the treatment groups were made to believe that 96 people had rated the headline before them and 75 of them were either Democrats or Republicans. We chose a fixed population of 96 to have a meaningful social signal that allows for easy calculations.
(3) *Social signal treatment(within-subjects)*: Participants in the treatment groups saw a social signal of those who had supposedly rated the headline before them. The social signal was manipulated to overwhelmingly (by a large majority, e.g. 72 versus 24) affirm two and overwhelmingly reject two Democrat- and Republican-consistent claims each. The social signal for the decoy headlines was more balanced to give a realistic impression of crowd deliberation.

Participants evaluated each claim by indicating whether they thought it was true or false. We allowed 20 seconds for each question and disabled the copying of headlines to prevent participants from looking them up. In addition, we conducted an attentiveness check at the beginning of the study and asked participants whether they had searched

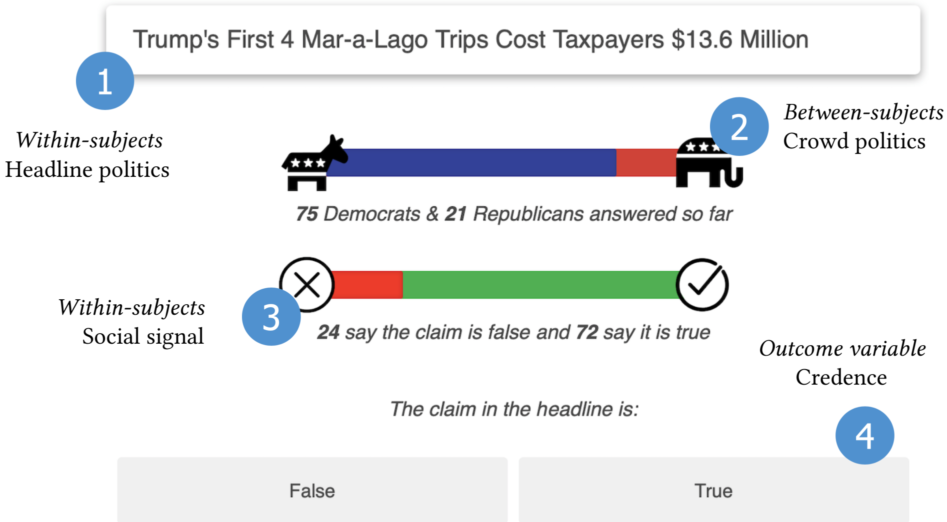

Fig. 2. Screenshot of the experiment annotated with manipulated variables and primary outcome.

online after completion. In the demographic section, participants indicated their gender, education, and age as well as their identification with political parties and ideologies.

3.3 News claim selection

The news headlines participants rated have been selected to (a) be representative of people's ordinary news consumption; (b) contain factual claims; (c) support either U.S. Democrat or Republican views; (d) be difficult to identify as true. To collect these headlines, we identified the top four liberal and conservative online news websites using Alexa traffic rank data[2]. We collected the 100 claims published by these organizations for every day between February 1st and 15th, 2019. From this initial pool of 10,660 headlines we computationally extracted the ones that were likely to contain a claim based on ClaimBuster scores [29], leaving 899 headlines. We then randomly sampled 40 headlines from each news organization, manually excluding headlines that did not contain a claim or were not related to U.S. politics. We asked workers (n=180) on Amazon Mechanical Turk to rate whether the remaining headlines aligned with U.S. Democrat or Republican views and whether they thought the claim in the headline was true. After dropping headlines that more than 75% of workers thought were true, we selected the 15 most pro-Democrat and the 15 most pro-Republican headlines for our study. In addition, we constructed a set of 12 decoy headlines that were shown to participants but were not part of the analysis. We collected ten non-political claims from the same sample, as well as two politically neutral false news claims from a prior study [45]. These easily discernible fake headlines served to assure workers that some of the headlines they were reviewing were indeed false. We randomized headline assignments for each participant. The full set of headlines is included in the project's Open Science Repository (https://osf.io/anonymized/).

[2]https://www.alexa.com/topsites/countries/US

3.4 Participants

We recruited 1,000 participants through Amazon Mechanical Turk (AMT)[15]. While not nationally representative, samples from AMT have been shown to reliably reproduce treatment effects in political research [18, 20] and behavioral research [37]. Recruitment was limited to U.S. participants of age 18+ with an approval rate of ≥ 98%. To counterbalance the over-representation of liberal-leaning workers on AMT, we posted part of our recruitment (n=250) as a task available for workers that identify as politically conservative only. Participants received compensation of $0.8 based on an estimated participation time of 4-5 minutes for a projected $10-12 hourly wage. Participants were debriefed upon study completion, explained the purpose of the study and the deception involved, and given the option to withdraw. The study protocols were approved by the Institutional Review Board at the primary investigator's university.

Our participant sample was politically balanced, with 47.8% of our participants identifying as politically right or right-center. Participants on average were 39.8 years old, 53.7% identified as female. We excluded participants who had failed an attentiveness check, participants who indicated they had searched for headlines on the web, and participants who rated all headlines as either true or false. We also deleted data of two participants who withdrew from the study, leaving us with a final sample of N=969 participants.

3.5 Open Science Repository

The full experimental data, analysis code and experiment preregistration are available at https://osf.io/anonymized/ and https://github.com/anonymized.

4 RESULTS

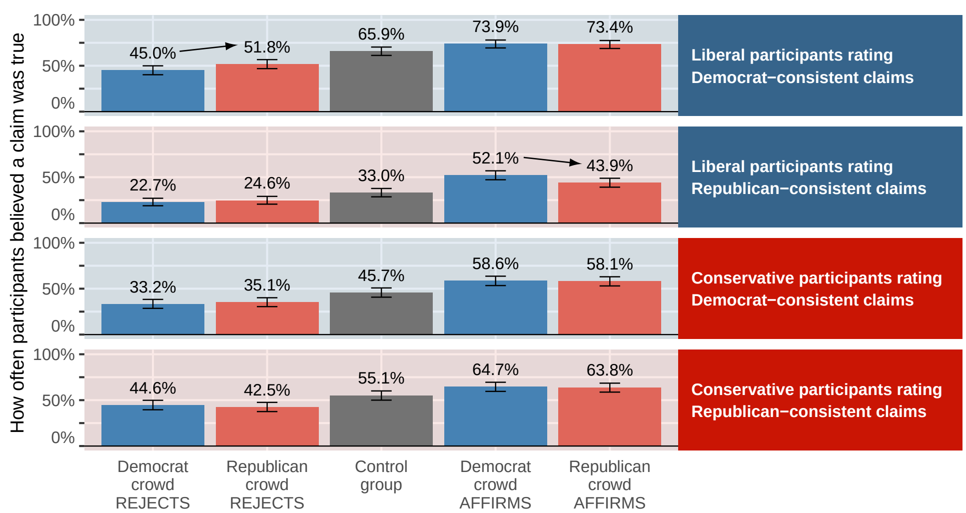

Fig. 3. How often participants believed a claim was true depending on the social signal from a political crowd (left to right), and their own political stance and the politics of the claim (top to bottom).

The results show that social influence is effective and primarily non-political (H1). They also provide some evidence for a combination of tribal (H2) and rational influence (H4). Figure 3 reports the aggregated evaluations of news headlines.

Table 1. Estimated model coefficients predicting participants' evaluations

	OLS	OR	OR 95% CI	Pr(>z)
1: (Intercept)	65.11	2.067	[1.74, 2.46]	0^{***}
2: Conservative participant	1.5	1.097	[1.00, 1.21]	0.06
3: Republican-consistent claim	-11.79	0.458	[0.36, 0.59]	0^{***}
4: Politically misaligned claim	-21.15	0.39	[0.32, 0.48]	0^{***}
5: Liberal : Social signal (H1)	12.4	1.765	[1.63, 1.91]	0^{***}
6: Liberal : Social signal : Crowd alignment (H2)	2.18	1.104	[1.02, 1.19]	0.01^{*}
7: Liberal : Social signal : Opportunity (H3)	-3.89	0.861	[0.73, 1.02]	0.08
8: Liberal : Social signal : Informativeness (H4)	1.56	1.068	[0.99, 1.15]	0.09
9: Conservative : Social signal (H1)	11.21	1.62	[1.50, 1.75]	0^{***}
10: Conservative : Social signal : Crowd alignment (H2)	-0.15	0.984	[0.91, 1.06]	0.68
11: Conservative : Social signal : Opportunity (H3)	-0.86	0.956	[0.81 ,1.10]	0.60
12: Conservative : Social signal : Informativeness (H4)	0.55	1.013	[0.94, 1.10]	0.74
13: σ		2.104	[1.84, 2.40]	0^{***}
N = 7,643, $P < .00001$, $\chi^2 = 472.85$, Log-likelihood = -4786.49				

Significance codes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The top two rows show the responses we received from liberal, left-leaning participants; the bottom two rows represent conservative participants. For each group, the first row represents evaluations of Democrat-consistent claims and the second row represents evaluations of Republican-consistent claims. We group data column-wise by the treatment group and the social signal. The center column shows responses in the control group where participants did not see a social signal. In the two leftmost columns, participants saw a social signal that rejected that claim, while in the two rightmost columns, the signal supported the claim. For example, the top left bar shows that liberal participants thought a Democrat-consistent headline was true 45% of the time when a majority-Democrat crowd rejected it, compared to 65.9% evaluating the same headlines as true when they saw no social signal (top middle bar, in gray). If the same headlines were rejected by a majority Republican crowd instead, liberals thought they were true 51.8% of the time (second-from-left, in red).

Our analysis proceeds as follows: first, we test whether the treatment groups answered significantly differently from the respective control group. Next, we test if there was a relative difference in evaluations between treatment groups when the signal came from a majority-Republican crowd versus a majority-Democrat crowd. Finally, we estimate the contributions of the different hypothesized types of influence in our model.

We find that across all 16 combinations of treatments and politics, participants significantly changed their evaluations when seeing a social signal. We see the smallest change for liberals evaluating a Democrat-consistent claim rejected by a majority-Republican crowd (first row; 65.9% to 73.4%; +7.5%, OR=1.42, p<0.05) and the largest change for liberals evaluating a Democrat-consistent claim rejected by a majority-Democrat crowd (first row; 65.9% to 45%; -20.9%, OR=0.42, p<0.001). Thus, we can confidently reject the null hypothesis (H0) that the social signal had no effect.

Now we turn to the differences within treatment groups due to the political makeup of the crowd. The only notable effects we find here are marked with arrows in the figure: liberals were more likely to change their view when a majority-Democrat crowd either rejected a Democrat-consistent claim (first row; 45% compared to 51.8%; +6.78%, OR=1.31, p<0.1) or affirmed a Republican-consistent claim (second row; 52.1% compared to 43.9%; -8.18%, OR=0.72, p<0.01). Note that we report absolute effects to allow comparisons to the graph while the statistics reported are based on two logistic models that estimate the significance of relative changes; the model specifications are included in the preregistration.

For the final part of the analysis, we convert the social signal into a continuous variable: -1 for rejection, 0 for the control group, 1 for affirmation. We create three composite variables that correspond to our hypotheses: (5) *Crowd alignment:* Does the participant politically identify with the crowd? (6) *Opportunity:* Does the social signal support the participant's prior beliefs? (7) *Signal informativeness:* Does the crowd vote against its own political agenda? We model hypotheses (H2) to (H4) through interactions terms of (5) to (7) and the social signal, and include effects of subject politics as well as claim politics. Note that since (H3) was not included in the preregistration, the model and following results should be considered exploratory.

The full model shown in Table 1. The baseline is a liberal participant evaluating a Democrat-consistent claim. We see that conservative participants did not evaluate headlines differently from liberal participants on average. However, the Republican-consistent headlines in our sample were overall less credible than the Democrat-consistent headlines. The largest change in evaluations is predicted by political misalignment with the claim: Participants were 21.5% less likely to rate a claim as true when it did not align with their political views (see line 4 in Table 1). For example, liberals believed Democrat-consistent claims 66% of the time, but Republican-consistent claims only 33% of the time in the control group, while only 12% of this difference is accounted for by 12% overall lower credibility of Republican-consistent headlines.

For both liberals and conservatives, we see an effect of social influence: the social signal raised or lowered their evaluations by about 12% compared to the control group, independently of crowd politics (line 5 and 9 in Table 1). In Figure 3, this corresponds to an average drop of ratings by 12% to the left and an average raise of 12% to the right of the control group (shown in grey). The model does not predict significant interactions between social influence and crowd politics for conservatives. However, the model is picking up on the differences between treatment groups for liberals we found in the analyses above, marked by arrows in the graph. In the model, they are accounted for as combination of tribal influence (H2, line 6 in Table 1) and rational influence (H4, line 8 in Table 1), corresponding to the observation that the social influence was about 8% stronger when liberals evaluate an informative signal from a majority-Democrat crowd. Finally, we see a hint of liberal selective influence in the model (H3, line 7 in Table 1), which may be due to floor and ceiling effects.

We calculated an observed power analysis for the model [27], finding that our experiment had 99.9% power at the level of main effects and one-way interactions; the power to detect two-way interactions was 40 to 70%.

5 DISCUSSION

Our results confirmed that people are highly polarized over political news claims in general. When participants saw a claim that did not align with their political views, they were 21% less likely to evaluate it as true, making political misalignment with a claim the principal predictor of disagreement. Such strong negative reactions to politically misaligned content have been observed in prior studies [28, 54] most recently showing that they affect news evaluations more than the source of the report [33].

At the same time, our study shows that individuals reliably respond to social influence even in polarized political settings. Both liberals and conservatives were highly influenced by the opinion of the crowd, regardless of its political makeup. They were about 12% more likely to evaluate a claim as true if the crowd supported it, and 12% less likely if the crowd rejected it. The robust appearance of both basic trends shows that our manipulation was effective. Our results indicate that the effect of social influence was largely independent of whether the participant identified with the crowd, or the social signal supported her political views, lending support to the idea of social influence as a non-political mechanism (H1). Indeed, conservatives in particular did not react to the political composition of the crowd in any notable way.

Liberals changed their opinions about 8% more for "informative" (in other words, unusual) signals from congenial crowds, that is, if a majority-Democrat crowd either rejected a Democrat-consistent claim or affirmed a Republican-consistent one. This observation suggests a tentative "tribal-rational" hypothesis: liberals were more influenced by informative social signals (H4), but only when the signals came from a majority-Democrat crowd (H2). We note that we did not see similar behavior by conservatives, raising the question of whether conservatives did not trust majority-Republican crowds or whether they did not reason about social signals the same way liberals did.

Our results indicate that motivated reasoning and cognitive dissonance reduction do not affect the influence of social signals. We found no support for selective influence (H3), where social influence would be stronger if a claim affirms pre-existing political views. Further, we also see no evidence of backfire effects.

5.1 Implications

Taken together, the findings of our study show that people have strong negative reactions to politically misaligned content, but not to social signals. This comparative "political blindness" of social influence is surprising and may open avenues for the design of depolarizing social signals.

Past attempts at reducing polarization by exposing people to a more balanced set of views have had mixed success due to the negative reactions evoked by politically misaligned content [5, 42, 58]. If individuals do not react to the *social signals* politically, we might be able to reduce polarization by exposing them to more balanced social ratings instead of balanced content. The challenge with today's rating systems is that due to the political clustering on social media sites [19, 39, 57], the aggregate opinions individuals see primarily come from politically congenial crowds. In this way, social influence and network homophily may reinforce each other [36, 40].

Given the "political blindness" of social influence established in this study, it may be possible to reduce political polarization on social media sites by "debiasing" social ratings. Techniques such as inverse probability weighting or methods developed to train recommender systems on biased data [49] may help create more balanced signals without overly exposing individuals to politically misaligned content. If people do not selective ignore debiased signals, this will lead to depolarization or at least not reinforce political clustering on social media sites. Debiasing social signals may be particularly relevant for crowdsourcing systems that evaluate political content [44]. The negative reactions to politically misaligned content make it hard to reach crowd agreement in political settings and produce results that are highly path- and crowd-dependent [36]. Through debiasing social ratings, one might be able to restore some "crowd wisdom."

5.2 Limitations

Our study has several important limitations. First, while our controlled environment supports the internal validity of our findings, our ecological validity may be more limited. In particular, we equally exposed participants to crowds that affirmed and rejected a social signal. While this manipulation isolated the effect of social influence from homophily, it does not represent people's experiences on social media sites. Second, expressive responding [33] or even demand characteristics [41] could be affecting our results, with participants providing answers that are not their true beliefs. However, we have analyzed the results separately for the subset of more politically extreme participants, which would be expected to be more prone to these biases, and found no shift in our results. Third, all claims in our study were real (and true) news headlines from relatively mainstream media sources. Our findings need to be extended to evaluating misinformation and to scenarios beyond news evaluation. Finally, we have exposed people to claims and signals only once and asked for their immediate evaluations. Our results do not allow inferences about cases of multiple or complex exposures [17] and their long-term effects.

6 CONCLUSION

We performed a novel online experiment to evaluate how social signals from a political crowd affect people's evaluations of political news claims. We find that while individuals tend to discard news claims that do not align with their political views, they were influenced by the social signal of the crowd independently of the crowd's political makeup or whether the signal supported their pre-existing views. While limited in ecological validity, our study and its potential future extensions may open up avenues for the design of depolarizing social rating systems.

REFERENCES

[1] Alan Abramowitz. 2010. *The disappearing center: Engaged citizens, polarization, and American democracy.* Yale University Press.

[2] Christopher H Achen and Larry M Bartels. 2017. *Democracy for realists: Why elections do not produce responsive government.* Vol. 4. Princeton University Press.

[3] Lisa R Anderson and Charles A Holt. 1997. Information cascades in the laboratory. *The American economic review* (1997), 847–862.

[4] Solomon E Asch. 1955. Opinions and social pressure. *Scientific American* 193, 5 (1955), 31–35.

[5] Christopher A Bail, Lisa P Argyle, Taylor W Brown, John P Bumpus, Haohan Chen, MB Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences* 115, 37 (2018), 9216–9221.

[6] Eytan Bakshy, Brian Karrer, and Lada A Adamic. 2009. Social influence and the diffusion of user-created content. In *Proceedings of the 10th ACM conference on Electronic commerce.* ACM, 325–334.

[7] Eytan Bakshy, Solomon Messing, and Lada A Adamic. 2015. Exposure to ideologically diverse news and opinion on Facebook. *Science* 348, 6239 (2015), 1130–1132.

[8] Delia Baldassarri and Andrew Gelman. 2008. Partisans without constraint: Political polarization and trends in American public opinion. *Amer. J. Sociology* 114, 2 (2008), 408–446.

[9] Pablo Barberá, John T Jost, Jonathan Nagler, Joshua A Tucker, and Richard Bonneau. 2015. Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological science* 26, 10 (2015), 1531–1542.

[10] Larry M Bartels. 2002. Beyond the running tally: Partisan bias in political perceptions. *Political behavior* 24, 2 (2002), 117–150.

[11] Michael A Beam, Myiah J Hutchens, and Jay D Hmielowski. 2018. Facebook news and (de) polarization: reinforcing spirals in the 2016 US election. *Information, Communication & Society* 21, 7 (2018), 940–958.

[12] Frank Bentley, Katie Quehl, Jordan Wirfs-Brock, and Melissa Bica. 2019. Understanding Online News Behaviors. (2019).

[13] Ellen Berscheid. 1966. Opinion change and communicator-communicatee similarity and dissimilarity. *Journal of Personality and Social Psychology* 4, 6 (1966), 670.

[14] Rod Bond and Peter B Smith. 1996. Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task. *Psychological bulletin* 119, 1 (1996), 111.

[15] Michael Buhrmester, Tracy Kwang, and Samuel D Gosling. 2011. Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on psychological science* 6, 1 (2011), 3–5.

[16] Pew Research Center. 2017. The Partisan Divide on Political Values Grows Even Wider. (2017).

[17] Damon Centola and Michael Macy. 2007. Complex contagions and the weakness of long ties. *American journal of Sociology* 113, 3 (2007), 702–734.

[18] Scott Clifford, Ryan M Jewell, and Philip D Waggoner. 2015. Are samples drawn from Mechanical Turk valid for research on political ideology? *Research & Politics* 2, 4 (2015), 2053168015622072.

[19] Michael D Conover, Jacob Ratkiewicz, Matthew Francisco, Bruno Gonçalves, Filippo Menczer, and Alessandro Flammini. 2011. Political polarization on twitter. In *Fifth international AAAI conference on weblogs and social media.*

[20] Alexander Coppock. 2018. Generalizing from survey experiments conducted on Mechanical Turk: A replication approach. *Political Science Research and Methods* (2018), 1–16.

[21] Dan Cosley, Shyong K Lam, Istvan Albert, Joseph A Konstan, and John Riedl. 2003. Is seeing believing?: how recommender system interfaces affect users' opinions. In *Proceedings of the SIGCHI conference on Human factors in computing systems.* ACM, 585–592.

[22] Chrysanthos Dellarocas. 2003. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management science* 49, 10 (2003), 1407–1424.

[23] Morton Deutsch and Harold B Gerard. 1955. A study of normative and informational social influences upon individual judgment. *The journal of abnormal and social psychology* 51, 3 (1955), 629.

[24] Leon Festinger. 1957. *A theory of cognitive dissonance.* Vol. 2. Stanford university press.

[25] Andreas Flache and Michael W Macy. 2011. Local convergence and global diversity: From interpersonal to social influence. *Journal of Conflict Resolution* 55, 6 (2011), 970–995.

[26] DJ Flynn, Brendan Nyhan, and Jason Reifler. 2017. The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology* 38 (2017), 127–150.

[27] Peter Green and Catriona J MacLeod. 2016. SIMR: an R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution* 7, 4 (2016), 493–498.

[28] William Hart, Dolores Albarracín, Alice H Eagly, Inge Brechan, Matthew J Lindberg, and Lisa Merrill. 2009. Feeling validated versus being correct: a meta-analysis of selective exposure to information. *Psychological bulletin* 135, 4 (2009), 555.

[29] Naeemul Hassan, Fatma Arslan, Chengkai Li, and Mark Tremayne. 2017. Toward automated fact-checking: Detecting check-worthy factual claims by ClaimBuster. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 1803–1812.

[30] Steffen Huck and Jörg Oechssler. 2000. Informational cascades in the laboratory: Do they occur for the right reasons? *Journal of Economic Psychology* 21, 6 (2000), 661–671.

[31] Young Eun Huh, Joachim Vosgerau, and Carey K Morewedge. 2014. Social defaults: Observed choices become choice defaults. *Journal of Consumer Research* 41, 3 (2014), 746–760.

[32] Shanto Iyengar, Gaurav Sood, and Yphtach Lelkes. 2012. " Affect, not ideology: A social identity perspective on polarization": Erratum. (2012).

[33] Maurice Jakesch, Moran Koren, Anna Evtushenko, and Mor Naaman. 2019. The Role of Source and Expressive Responding in Political News Evaluation. *Computation and Journalism Symposium 2019* (2019).

[34] H.C. Kelman. 1961. Processes of opinion change. *Public Opinion Quarterly* 25 (1961), 57–78.

[35] Ziva Kunda. 1990. The case for motivated reasoning. *Psychological bulletin* 108, 3 (1990), 480.

[36] Michael Macy, Sebastian Deri, Natalie Tong, and Alexander Ruch. 2019. Opinion Cascades and the Unpredictability of Partisan Polarization. (2019).

[37] Winter Mason and Siddharth Suri. 2012. Conducting behavioral research on AmazonâĂŹs Mechanical Turk. *Behavior research methods* 44, 1 (2012), 1–23.

[38] Winter A Mason, Frederica R Conrey, and Eliot R Smith. 2007. Situating social influence processes: Dynamic, multidirectional flows of influence within social networks. *Personality and social psychology review* 11, 3 (2007), 279–300.

[39] Miller McPherson, Lynn Smith-Lovin, and James M Cook. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology* 27, 1 (2001), 415–444.

[40] Lev Muchnik, Sinan Aral, and Sean J Taylor. 2013. Social influence bias: A randomized experiment. *Science* 341, 6146 (2013), 647–651.

[41] Austin Lee Nichols and Jon K Maner. 2008. The good-subject effect: Investigating participant demand characteristics. *The Journal of general psychology* 135, 2 (2008), 151–166.

[42] Brendan Nyhan and Jason Reifler. 2010. When corrections fail: The persistence of political misperceptions. *Political Behavior* 32, 2 (2010), 303–330.

[43] Eli Pariser. 2011. *The filter bubble: How the new personalized web is changing what we read and how we think*. Penguin.

[44] Gordon Pennycook and David Rand. 2018. Crowdsourcing judgments of news source quality. *SSRN. com* (2018).

[45] Gordon Pennycook and David G Rand. 2018. Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. *Cognition* (2018).

[46] Emily Pronin, Jonah Berger, and Sarah Molouki. 2007. Alone in a crowd of sheep: asymmetric perceptions of conformity and their roots in an introspection illusion. *Journal of personality and social psychology* 92, 4 (2007), 585.

[47] Daniel M Romero, Brendan Meeder, and Jon Kleinberg. 2011. Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter. In *Proceedings of the 20th international conference on World wide web*. ACM, 695–704.

[48] Matthew J Salganik, Peter Sheridan Dodds, and Duncan J Watts. 2006. Experimental study of inequality and unpredictability in an artificial cultural market. *science* 311, 5762 (2006), 854–856.

[49] Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, and Thorsten Joachims. 2016. Recommendations as treatments: Debiasing learning and evaluation. *arXiv preprint arXiv:1602.05352* (2016).

[50] Cosma Rohilla Shalizi and Andrew C Thomas. 2011. Homophily and contagion are generically confounded in observational social network studies. *Sociological methods & research* 40, 2 (2011), 211–239.

[51] John Sides and Daniel J Hopkins. 2015. *Political polarization in American politics*. Bloomsbury Publishing USA.

[52] Herbert W Simons, Nancy N Berkowitz, and R John Moyer. 1970. Similarity, credibility, and attitude change: A review and a theory. *Psychological Bulletin* 73, 1 (1970), 1.

[53] Rune Slothuus and Claes H De Vreese. 2010. Political parties, motivated reasoning, and issue framing effects. *The Journal of Politics* 72, 3 (2010), 630–645.

[54] Natalie Jomini Stroud. 2010. Polarization and partisan selective exposure. *Journal of communication* 60, 3 (2010), 556–576.

[55] Cass R Sunstein. 2018. *# Republic: Divided democracy in the age of social media*. Princeton University Press.

[56] Charles S Taber and Milton Lodge. 2006. Motivated skepticism in the evaluation of political beliefs. *American Journal of Political Science* 50, 3 (2006), 755–769.

[57] Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. *Science* 359, 6380 (2018), 1146–1151.

[58] Thomas Wood and Ethan Porter. 2019. The elusive backfire effect: Mass attitudes' steadfast factual adherence. *Political Behavior* 41, 1 (2019), 135–163.