Personalized Rankings and User Engagement: An Empirical Evaluation of the Reddit News Feed

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Abstract

Digital platforms increasingly curate their content through personalized algorithmic rankings. Given the limited attention of their users and reliance on advertising, platforms have an incentive to promote content that increases the predicted engagement of each user. However, managers must also balance maximizing total engagement with the quality of content promoted on the platform due to advertiser concerns over brand safety and to satisfy policy makers. This paper studies how maximizing engagement for each user affects the quality of content with which users engage to understand the extent to which engagement-maximizing algorithms promote and incentivize low-quality content. In addition, I evaluate how the ranking algorithm itself can be designed to promote and encourage engagement with high quality content. To do this, I study the Reddit politics community and exploit a novel discontinuity – revealed in Reddit's code repository – in how the ranking algorithm orders posts to identify the effect of a post's rank on the number of comments it receives. I use this discontinuity to identify a discrete choice model of user comment decisions and estimate the distribution of news that users are exposed to and comment on under a personalized algorithm that maximizes engagement. This counterfactual demonstrates that personalization drives a wedge between users in terms of the quality of content – the credibility rating of an article's publisher – with which are exposed and engage. Under the personalized ranking algorithm, users who ordinarily engage with high-credibility publishers continue to do so. However, users who ordinarily engage with lower-credibility publishers are exposed to and engage with an even larger share of low-credibility publishers under the personalized engagement-maximizing algorithm. Finally, I evaluate a credibility-aware algorithm that explicitly promotes credible news publishers and find that moving to the credibility-maximizing algorithm reduces total engagement by 5.0%, a meaningful decline. Yet, platforms can increase the share of the average user's engagement with high-credibility publishers by 6.8 percentage points for only a 2.0% decrease in engagement. These findings suggest that algorithmic interventions can be a useful tool to promote higher-quality content to help satisfy both advertisers and policy makers.

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1 Introduction

Digital platforms curate content for their users because of limited user attention and the vast amount of available content. The advertising business model adopted by many platforms creates an incentive to promote content through ranking algorithms that predict what content users are most likely to act on via clicking, liking, or commenting [Thorburn et al., 2022, Narayanan, 2023]. Personalized ranking algorithms that optimize for such engagement metrics may also promote low-quality or problematic content [Orlowski, 2020], which can negatively impact platforms if concerns over brand safety lead advertisers to respond by reducing advertising spending [Ahmad et al., 2023] or if there is a disconnect between short-term engagement metrics and long-term user welfare [Spence and Owen, 1977, Kleinberg et al., 2022, Allcott et al., 2022, Agan et al., 2023]. Moreover, concerns that ranking algorithms promote and incentivize low-quality content have prompted policy makers around the world to consider regulating ranking algorithms. Therefore, managers must balance maximizing engagement with the health of the platform ecosystem to satisfy both internal and external stakeholders.

There is an active debate surrounding the benefits and potential risks of personalized rankings that optimize for engagement. Platform managers often contend that ranking algorithms act as agents for users by promoting a user's preferred content and reducing search frictions on the platform [Dorsey, 2022]. Critics, however, frequently raise concerns that optimizing for engagement can incentivize low-quality content and reduce the diversity of viewpoints to which users are exposed [Pariser, 2011, Orlowski, 2020]. Despite these competing narratives, the impact of personalized news feeds on the quality of content users engage with remains an important and largely unresolved question. The lack of evidence regarding these issues primarily stems from the substantial challenges to studying ranking algorithms on social media platforms, including platforms' hesitance to share data and experiments with external researchers [Eckles, 2022].

This paper studies the impact personalized ranking algorithms that optimize for engagement have on the quality of content that is promoted to users and with which users engage. I explore this question in the context of political news on Reddit. In particular, I focus on the platform's largest politics community that centers on sharing and discussing articles about US political news. In this community, users share news articles about US politics and then engage in discussion and commentary in comment threads alongside each article. I use the number of comments an article receives as the primary measure of engagement.

The Reddit politics community I study provides an ideal laboratory to analyze the types of content that get promoted under alternative ranking algorithms. The community is important to the platform due its size and the strong preferences of advertisers to not appear alongside low-quality news content [Ahmad et al., 2023].[1] In addition, it is often challenging to evaluate the

[1] The politics community is consistently ranked as one of the most active communities on the platform.

quality of content on social media. Studying the politics community, which focuses on discussing news articles, allows me to use established measures of publisher credibility as a neutral measure of quality [Lin et al., 2022].[2] Moreover, this community contains substantial heterogeneity in content quality – the credibility rating of the article's publisher – and horizontal differentiation in content based on the political slant of the article's publisher. There is also substantial heterogeneity in user preferences. Taken together, these sources of heterogeneity, which are common on many social media platforms, make it difficult to predict ex-ante what impact personalization and optimizing for engagement will have on the quality of content that is promoted.

To study the impact of ranking algorithms on the type of content to which users are exposed and with which they engage I employ two complementary approaches. First, I train a collaborative filtering based recommender system that is trained on historical engagement patterns. The primary benefit of this approach is that it is able to use a much larger set of users to train and evaluate the model. In the second approach, I estimate a micro-founded choice model of individual engagement decisions and estimate engagement patterns under counterfactual ranking algorithms. The choice-model approach directly addresses the limitations of the recommender system and allows me to quantify counterfactual algorithms' impact on actual engagement decisions. This richer analysis makes the choice-model the preferred approach and the recommender system serves to strengthen the argument that the findings generalize to a broader set of users. To identify the choice model, I use both individual engagement decisions and reduced-form estimates of the causal effect of post rank on future engagement. I organize the analysis by first estimating the causal effect post rank has on engagement. Second, I train and analyze the recommender system. Finally, I estimate the choice model and study engagement patterns under counterfactual ranking algorithms.

Throughout the analysis, a central challenge will be that a post's rank – its position in the feed – is endogenous. One should be concerned that a post's potential outcomes are correlated with its position in the feed, as I expect the existing feed to promote posts that are more 'commentable' relative to posts that are not promoted. Therefore, to identify position effects – the causal effect a post's position has on the number of comments it receives – I exploit a novel regression discontinuity revealed in an open-source mirror of the platform's code base. This open-source mirror allows me to inspect the ranking algorithm and recreate the numerical score that is used to rank posts. Consequently, this permits using a regression discontinuity design to identify the local average treatment effect of a post's rank on the number of comments it receives in a period. As the ranking score of a focal post passes the score of a competing post, there is a discontinuous jump in the probability the focal post is ranked lower on the page.[3] The treatment effect estimates suggest that

[2] Note in this paper I use the term content quality to describe quality from the perspective of platform managers. Publisher credibility is a relevant quality measure for platform managers because the platform's many stakeholders, including advertisers, employees, and policy makers care about credibility.

[3] This identification strategy is most closely related to Narayanan and Kalyanam [2015], where data on the AdRank scores in Google auctions are used to estimate the position effects on Google advertisements, though to my knowledge this is the first application of such a strategy to a social media setting.

the causal effect of a post being promoted from the second position in the feed to the first position results in a 43.6% increase in the number of comments the post receives in a period. The effect of being promoted declines further down the feed, as the causal effect of moving one position higher on the feed is largest for the first position.

With an identification strategy for position effects, I turn to understanding the impact of optimizing for engagement with personalized rankings on the type of content to which users are exposed and with which they engage. First, I train a collaborative filtering recommender system for implicit feedback that uses data on user-level comments to learn low-dimensional embeddings of users and publishers [Hu et al., 2008]. The model then recommends articles by publishers that the embeddings suggest a user is most likely to engage with. By showing that the recommender system predicts treatment effects, I validate the model and verify it contains useful information about user preferences. I then study what publishers the recommender system would recommend to each user within each period. My findings show that the recommender system promotes publishers that are less politically diverse than those promoted by the existing algorithm and recommends content of heterogeneous quality to users. The majority of users are recommended more high-quality publishers compared to the existing algorithm, though an important subset of users are recommended low-quality publishers in over half of the periods. While unable to estimate the impact on engagement, this recommender system approach presents my first set of results to suggest personalizing rankings to maximize engagement decreases the diversity of publishers to which users are exposed and drives a wedge between users along the credibility dimension.

The drawbacks of the recommender-system approach are addressed directly in the second approach, where I estimate a micro-founded choice model of user comment decisions. I model engagement decisions based on two components: whether a user is exposed to a post and whether their utility from commenting conditional on exposure exceeds the utility of the outside option. Post rank impacts engagement in this model only through the exposure component, where the probability of being exposed to a post depends on the post's rank. Conditional on exposure, users then have heterogeneous preferences to comment on posts depending on the political slant and credibility rating of the publisher. This model is identified using the regression discontinuity position effect estimates and individual engagement choices. I use the model to estimate engagement patterns under counterfactual ranking algorithms including both personalized and non-personalized engagement maximization. In addition, I evaluate an alternative credibility-aware ranking algorithm that optimizes for an objective function that balances total engagement and engagement with high-quality publishers.

The recommender system and choice model approaches yield similar results though the counterfactual analysis, which is based on the discrete choice model, allows for a richer understanding of the effects on engagement. I find that personalization exacerbates differences in the share of user engagement with high-credibility publishers. Both approaches suggest personalization tends to promote high-credibility publishers to users engaging with high-credibility publishers under Reddit's actual ranking algorithm and promotes lower-credibility publishers to users engaging with less-credible publishers under the actual ranking algorithm. This result indicates that personalization drives a wedge between users along the quality dimension and can lead to a subset of users being responsible for much of the engagement with low-quality content on the platform. Moreover, I find that personalized engagement maximization leads to engagement with publishers that are less politically diverse and more similar to publishers the user has engaged with previously.

The discrete choice model of user engagement also permits analysis of engagement patterns under alternative objective functions that explicitly trade-off total engagement and engagement with high-credibility publishers. At one extreme, this nests a credibility-maximizing algorithm that maximizes engagement with high-credibility publishers. This algorithm leads to a meaningful 5.0% decline in total user engagement. That said, platforms can achieve over half of the increase in news diet quality – the share of a user's engagement with high-credibility publishers – from the credibility-maximizing algorithm for a more modest 2.0% decrease in engagement. This change in engagement is similar in magnitude to the difference between the personalized and non-personalized engagement-maximizing algorithms. However, the non-personalized algorithm does not meaningfully improve the quality of user news diets, while the credibility-aware algorithm increases the average user's share of engagement with high-credibility publishers by 6.8 percentage points. This suggests there is room for managers to balance the competing objectives of maximizing total engagement and improving the health of the platform's ecosystem, and the ranking algorithm appears to be a useful tool to achieve such balance. Moreover, these findings highlight the potential benefits of personalization, as the personalized credibility-aware algorithm permits the platform to substantially increase the quality of publishers promoted for the same quantity of engagement as the non-personalized engagement-maximizing algorithm.

A benefit of focusing on comments as the measure of engagement is the ability to analyze the text content to evaluate how comment sentiments change under counterfactual ranking algorithms. The results suggest that both the personalized and non-personalized engagement-maximizing algorithms slightly elevate the share of negative comments for the average user. Personalization, however, increases the dispersion of negative comment shares relative to the non-personalized algorithm. On average, users who prefer low-credibility publishers have the largest increases in their negative-sentiment engagement shares under the personalized algorithm. Given that negative comments contain strong negative emotions such as disgust and anger and are more likely to be classified as toxic, this finding suggests when low-credibility outlets drive user engagement it increases the likelihood of low-quality discussion.

Related Literature

This paper contributes to three strands of the literature. A large literature has studied the impact of algorithmic recommendations on consumers. This literature considers algorithmic recommendations' impact on product sales [Fleder and Hosanagar, 2009, Oestreicher-Singer and Sundararajan, 2012, Hosanagar et al., 2014, Ghose et al., 2014, Lee and Hosanagar, 2019, Donnelly et al., 2023, Wang et al., 2023], content consumption [Claussen et al., 2021, Holtz et al., 2020, Aridor et al., 2022, Chen et al., 2023], the informational content of recommendations [Aridor et al., 2022], and consumer welfare [Ghose et al., 2014, Chaney et al., 2018, Donnelly et al., 2023]. In addition, this literature investigates how ranked feeds on social media platforms impact individual well-being [Kramer et al., 2014], media consumption [Bakshy et al., 2015, Levy, 2021, Dujeancourt et al., 2021], and exposure to content from politicians [Huszár et al., 2022]. Much of this literature explores the impact of algorithmic ranking on the diversity of consumption [Van Alstyne and Brynjolfsson, 2005, Fleder and Hosanagar, 2009, Claussen et al., 2021, Holtz et al., 2020, Berman and Katona, 2020, Chen et al., 2023] or product sales [Oestreicher-Singer and Sundararajan, 2012, Hosanagar et al., 2014, Lee and Hosanagar, 2019] and how likely users are to be exposed to cross-cutting news publishers [Bakshy et al., 2015, Levy, 2021]. Most related to this paper, Huszár et al. [2022] analyzes an experiment on Twitter that randomly assigns a group of Twitter users to receive a reverse chronological ranking algorithm compared to those that received the existing personalized algorithm. Huszár et al. [2022] find that Twitter's personalized algorithm amplified right-leaning publishers. This is consistent with my finding that right leaning publishers see the largest increase in engagement in the personalized engagement-maximizing algorithm. A novel contribution of the modeling-based approach taken here is that it allows me to evaluate alternative algorithms including a credibility-aware algorithm that balances optimizing for total engagement with engagement with high-credibility publishers. I also contribute to this literature by studying how personalized news feeds that optimize for engagement affect the quality of publishers with which users engage in addition to the slant of publishers.

A second strand of related literature studies the impact of news aggregators on publishers and users [Das et al., 2007, Athey and Mobius, 2012, Chiou and Tucker, 2017, George and Hogendorn, 2020, Athey et al., 2021, Amaldoss and Du, 2023]. This literature focuses on understanding how news aggregators, such as Google News, shape the news industry and user consumption habits. Social media platforms, and the Reddit politics community in particular, have many similarities to news aggregators, as community members share and discuss articles from many different publishers. To the extent that this literature has studied personalization, it has focused on changes in engagement [Das et al., 2007] and visits to local news publishers [Athey and Mobius, 2012, George and Hogendorn, 2020]. I contribute to this literature by studying the impact of the order of publishers within a feed on the quality and diversity of publishers with which users engage.

Finally, this paper contributes to the large and growing literature studying interventions to improve the quality of information people consume online. This literature both documents the reach of misinformation on social media and how it spreads [Allcott and Gentzkow, 2017, Vosoughi et al., 2018, Grinberg et al., 2019, Guess et al., 2019, 2020] and evaluates interventions to curb the spread of misinformation (see Pennycook and Rand [2021] and Lazer et al. [2018] for a review). My findings are consistent with the literature showing that a minority of users consume the majority of misinformation, and I contribute to the literature by finding that personalized engagement-maximizing algorithms exacerbate this difference [Allcott and Gentzkow, 2017, Grinberg et al., 2019, Guess et al., 2019, 2020]. In addition, this literature assesses many behavioral interventions through both lab and field experiments. That said, empirical evaluations of algorithmic interventions have been more difficult given limited access to platform data. I contribute to this literature by exploring how ranking algorithms affect the quality of news with which users engage. More specifically, I study how personalization heterogeneously impacts the quality of users' news diets and consider how algorithmic interventions can improve the quality of news users engage with for all users. To my knowledge, this is among the first work to empirically estimate, in a real-world-setting, the costs platforms would incur by down-ranking low-quality content.

Implications for Managers and Policy Makers

These findings have important managerial implications. Given advertiser concerns over brand safety and reluctance to appear alongside low-quality publishers [Ahmad et al., 2023], platform managers must balance total engagement with the quality of content being promoted to users. Additional internal and external stakeholders, including policy makers and platform employees, have also demonstrated interest in reducing the spread of low-quality content on digital platforms [Warner, 2023, Haugen, 2021]. The results presented here suggest codifying the trade-off explicitly in the objective function of the ranking algorithm is an effective method for limiting the spread of low-quality content. Moreover, I estimate the cost of including credibility in the objective function and find that platforms willing to accept a modest decline in total engagement can substantially increase the share of engagement with high-quality publishers.

The findings also have important implications for policy makers. Concerns regarding ranking algorithms promoting and incentivizing low-quality content have prompted policy makers around the world to consider regulation that can address these issues. A common regulatory approach is to require platforms to allow users to opt out of personalized recommendations. The European Union's Digital Services Act includes such provisions, as do proposed laws in the United States such as the Filter Bubble Transparency Act. Related proposals in the United States that limit Section 230 protections for personalized recommendations would likely have a similar effect (e.g. Justice Against Malicious Algorithms Act, and the Protecting Americans from Dangerous Algorithms Act). The implications of this study are clear: ranking algorithms can be designed to improve the quality of the content users engage with, and personalization is a valuable tool to mitigate the cost of moving away from optimizing only for engagement. A solution that takes advantage of the benefits of personalization, while protecting individual autonomy, would be to allow users to adjust the weights on different components within the ranking algorithm objective function, including the weight placed on publisher credibility. What weights users would choose and the results of such a design remain open questions and merit future work. Alternatively, regulators could incentivize platforms to align their ranking objective function with the preferences of society to take advantage of personalized ranking algorithms' substantial benefits while mitigating their harms.

2 Background and Data

Reddit is a large social news aggregator with over 50 million daily active users as of January 2020.[4] The platform is organized into over 100,000 virtual communities called subreddits that are focused on sharing and discussing content related to the community's topic. In this study, I focus on a subset of communities that are centered around sharing and discussing news articles. In these communities, users share news articles and then discuss the articles in comment threads as seen in Figure 1. Reddit is structured such that users can submit two types of content, submissions and comments. In the communities studied, submissions must contain a link to a news article and I therefore use the terms submissions, articles, and posts interchangeably. Users then discuss articles by posting comments – this commenting activity is the primary engagement measure I study.

2.1 Algorithmic Feeds on Reddit

Users interact with content on the platform via algorithmic feeds of a few different forms. Any user who visits a community page will see submissions from the community ranked by the platform's default ranking algorithm.[5] This algorithm sorts submissions according to the post's age and vote score – the net number of upvotes minus downvotes on a post – and is described in more detail in Section 3. In addition to the default algorithm, users can choose to rank posts according to several alternative algorithms. The *new* algorithm implements a reverse chronological ranking; the *top* algorithm ranks posts according to the vote score in a given period; the *rising* algorithm favors recent posts; and the *controversial* algorithm promotes posts that have received more votes, either up or down, regardless of their direction. This paper focuses on the default algorithm's impact on engagement. All analyses presented here condition on the alternative algorithm rankings remaining unchanged. That is, when estimating the impact of post rank on engagement I estimate counterfactuals where post rank changes in the default feed but not in the alternative feeds.

[4] `https://www.redditinc.com/`

[5] On the platform, this default algorithm is called the *hot* algorithm. I refer to the hot algorithm as the actual ranking algorithm throughout.

In addition, Reddit users can join communities. Posts from these communities are displayed on a user's Home feed, the default feed users encounter when visiting the platform. The Home feed sorts posts according to the same default algorithm used by individual communities but ranks posts from all communities that a user is a member of rather than only posts from a single community.[6] The Home feed has important implications for this analysis, as I estimate the effect a post's rank in the subreddit feed has on its engagement and estimate engagement patterns under alternative rankings. Importantly, this captures both the direct effect of changing a post's rank on the subreddit feed and the indirect effect of changing the rank on the Home feed, holding fixed posts from other communities. For example, if two posts from the politics feed (A and B) and one post from another community (C) are ranked A, C, B on the Home feed, then counterfactuals where post B is promoted on the politics community correspond to the counterfactual ranking B, C, A on the Home feed. Given the prominence of the Home feed, it is important that the position effect estimates and counterfactual analyses include the effect of post rank in the Home feed.

2.2 Data

2.2.1 Ranking and Engagement

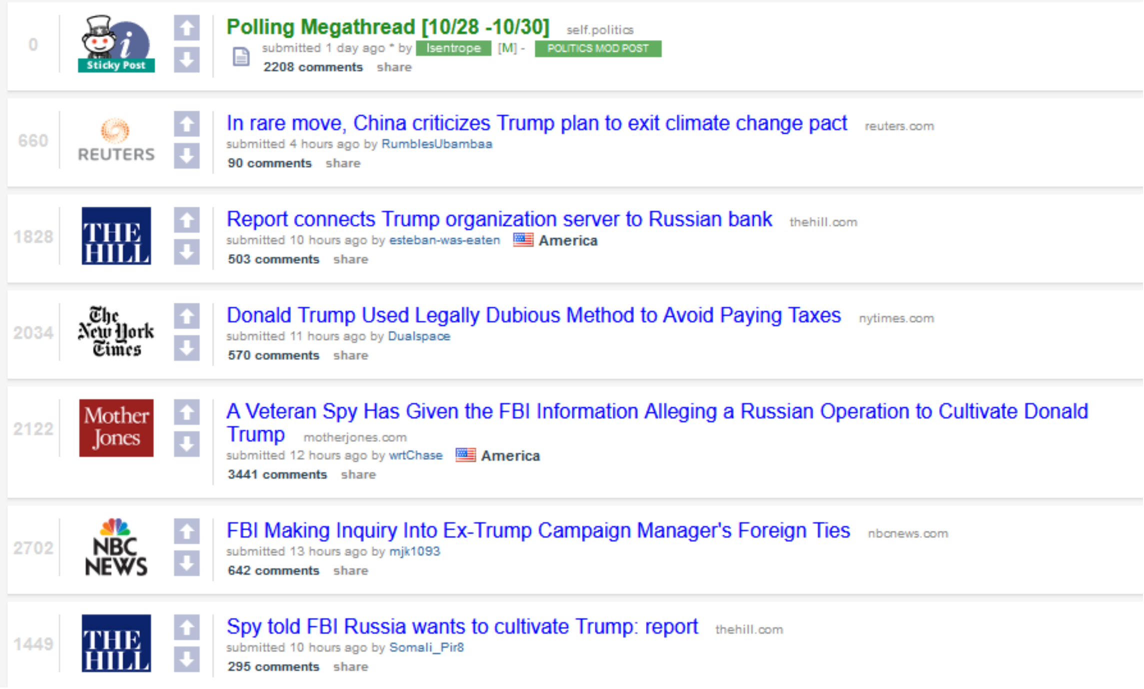
I merge data from several sources in this study. First, I scrape subreddit landing pages from the Internet Archive's Wayback Machine for each subreddit in the study. These data provides historical snapshots of subreddit feeds, allowing me to collect the top 25 ranked posts, their position in the feed, and post features. A snapshot from the politics community following the 2016 election is shown in Figure 1. Alongside the post position in the feed, parsing the Wayback Machine snapshots provides the age of a post, number of existing comments, vote score of each post (net number of upvotes minus downvotes), post title, and domain the post links to, if any. In addition, each snapshot reveals the number of subscribers each community has and the number of users online at the time of the snapshot.

Submissions on Reddit are either pinned to the top of the feed by community moderators or ranked organically.[7] I will focus on organic posts displayed in blue in Figure 1. These posts are submitted by users and ranked according to the algorithms described in Section 2.1. In the set of news-related communities considered here, posts are typically required to follow strict community guidelines: they must be on topic for the community, they must link to an article from a news publisher, and the post title must exactly match the headline of the article to which the post links. Any commentary on the article must be added in the comment sections, which I turn to next.

[6] In 2018, after the period studied, Reddit changed the default algorithm used by the Home feed to the Best algorithm, as described in `https://www.reddit.com/r/changelog/comments/7spgg0/best_is_the_new_hotness/`.

[7] Posts pinned by moderators are shown in green and are typically threads created to discuss the major events of the day. Importantly, these are not algorithmically ranked and I condition on these posts remaining in their position on the feed. That is, I only consider counterfactuals where the organic post positions change.

Figure 1: Snapshot of Politics Community



0 Sticky Post
Polling Megathread [10/28 -10/30] self.politics
submitted 1 day ago * by Isentrope [M] - POLITICS MOD POST
2208 comments share

660 REUTERS
In rare move, China criticizes Trump plan to exit climate change pact reuters.com
submitted 4 hours ago by RumblesUbambaa
90 comments share

1828 THE HILL
Report connects Trump organization server to Russian bank thehill.com
submitted 10 hours ago by esteban-was-eaten America
503 comments share

2034 The New York Times
Donald Trump Used Legally Dubious Method to Avoid Paying Taxes nytimes.com
submitted 11 hours ago by Dualspace
570 comments share

2122 Mother Jones
A Veteran Spy Has Given the FBI Information Alleging a Russian Operation to Cultivate Donald Trump motherjones.com
submitted 12 hours ago by wrtChase America
3441 comments share

2702 NBC NEWS
FBI Making Inquiry Into Ex-Trump Campaign Manager's Foreign Ties nbcnews.com
submitted 13 hours ago by mjk1093
642 comments share

1449 THE HILL
Spy told FBI Russia wants to cultivate Trump: report thehill.com
submitted 10 hours ago by Somali_Pir8
295 comments share

Note: A Wayback Machine snapshot of the politics subreddit from November 2016. Posts pinned by moderators are shown in green and are typically threads created to discuss major events or frequent discussion topics such as polling. Posts in blue are algorithmically ranked organic posts that are the focus of this study.

The primary engagement metric I consider is comments on articles. Reddit is a platform to share and discuss user-generated content. Comments themselves are a form of user-generated content that bring people to the platform, and encouraging additional comments is of direct interest to the platform [Burke et al., 2009]. In addition, experimental evidence suggests users who receive comments on their posts are more likely to generate content in the future, a finding that further indicates encouraging more comments is an outcome of interest for Reddit [Eckles et al., 2016, Mummalaneni et al., 2022]. Moreover, there is correlational evidence that users who comment more also spend more time on social media platforms – a metric that more closely approximates the amount of advertisements the user sees [Wojcik and Hughes, 2019]. I merge data from Baumgartner et al. [2020] that contain a near-universe of submissions and comments to public Reddit communities to generate the engagement outcomes. These data contain user-level commenting behavior, where each comment includes a time-stamp, the full text of the comment, the post the comment is responding to, and the vote-score the comment received, among other observables. This information allows me to reconstruct a post's full comment history, including the comments that directly follow each of the Wayback Machine's snapshots.

These data on user comments serve several purposes. First, they allow me to construct the number of comments each post received in a window following each snapshot. This will be critical for estimating position effects on the platform. Second, individual-level comment decisions are used to estimate a choice model of user engagement in Section 5. Here, the panel nature of the data allows me to identify rich user-level heterogeneity in comment preferences. Finally, studying comments allows me to analyze the text content to provide additional insight into user preferences and to understand how optimizing for engagement impacts the sentiment of comments submitted to the platform.

2.2.2 Publisher Ratings

I also collect publisher ratings to understand the characteristics of an article's publisher. I use two sets of ratings. First are publisher political slant measures [Robertson et al., 2018] that represent the relative propensity of a domain being shared on Twitter by known Democratic party members relative to known Republican members, ranging from -1 to 1. A slant rating of -1 represents a domain that is only shared by Democrats while a slant rating of 1 represents a domain that is only shared by Republicans. Robertson et al. [2018] demonstrate this measure is consistent with a number of other expert, crowd-sourced, and audience-based ratings [Bakshy et al., 2015, Budak et al., 2016]. A primary benefit of the Robertson et al. [2018] scores compared to other measures of publisher slant is the high coverage, as the data set includes ratings for over 19,000 domains. This results in high coverage in our data, with over 90% of posts in the politics community containing a link to a publisher matching a domain in the Robertson et al. [2018] data. The coverage is lower for other news categories, as some categories have less strict rules around sharing news articles and allow links to smaller websites such as sports blogs. The politics community, however, is the focus of this study and the other categories are only used to improve power in identifying position effects. I discretize publisher slant into quintiles when looking at the impact of personalization on slant diversity. The primary outcome for slant diversity is the first-order Wasserstein distance of engagement or promotion shares across these five bins of publisher slant relative to a uniform distribution. This distance metric is more appropriate than other common measures of diversity used in the literature, including the Herfindahl-Hirschman Index and Shannon Entropy given the ordered nature of slant partitions. For example, the Wasserstein distance between a user's engagement and the uniform distribution is larger (i.e. less diverse) for a user who engages only with publishers from a politically slanted partition versus a user only engaging with moderate publishers. The distance is minimized when users engage equally with publishers from all slant partitions and is largest when only engaging with publishers from a politically extreme partition.

I also use credibility ratings, described in Lin et al. [2022], for over 11,520 news publishers. Lin et al. [2022] aggregate individual ratings from six rating organizations and demonstrate substantial agreement among individual sources. Importantly, the ratings released alongside Lin et al. [2022] show an extremely high correlation with NewsGuard ratings, a proprietary set of publisher ratings that employ extensive criteria including accuracy and balance of reporting, a process of publishing corrections, clear separation of opinion articles, and transparency of perceived conflicts. Figure 2 plots the joint distribution of publisher slant score and credibility rating for publishers that appear in at least 1% of the snapshots in the politics community. Table A.1 shows these ratings for six example domains. In evaluating user news diets, I will discretize the credibility ratings into high- and low-quality publishers for ease of interpretation. When doing so, I classify publishers as high quality if their credibility rating is greater than 0.65 and I show robustness of key results to other thresholds in Appendix Section C.4.[8]

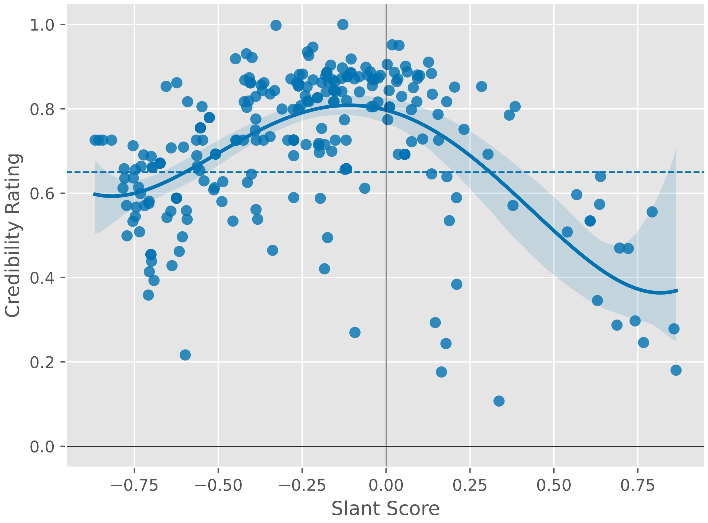
2.3 Textual Analysis of Comment Text

A unique benefit of studying comments as the focal measure of engagement is that I can analyze the textual content in order to understand the types of comments users are submitting to the platform and how this varies depending on the article. This sentiment analysis is used in the micro-founded choice model as I allow users to choose the sentiment of their comment conditional on article features. I use these estimates to evaluate the extent to which optimizing for engagement leads to deterioration in discussion quality.

I analyze the sentiment and emotional content of comments using a pre-trained neural network for sentiment analysis and emotion detection. The pre-trained neural network, which is described in Pérez et al. [2021], uses embeddings generated using the language model BERTweet [Nguyen

[8] The threshold of 0.65 is chosen as it is the median Lin et al. [2022] credibility rating within the Medium credibility category of Media Bias Fact Check, a professional rating organization.

Figure 2: Joint Distribution of Publisher Credibility and Slant Scores



Note: This figure plots the joint distribution of publisher slant score and credibility rating for the set of publishers that appear in at least 1% of the snapshots in the politics community. The dotted line displays the cutoff for high-credibility publishers. The regression line is a fourth-order polynomial fit. Confidence bands represent 95% confidence intervals.

Table 1: Summary Statistics

	Number	Share of Posts Missing			Number of Comments			
	Snapshots	Domain	Slant	Credibility	5 Min	10 Min	20 Min	60 Min
Politics	2104	0.01	0.07	0.11	2.98	5.97	11.93	35.76
US/World	4771	0.00	0.08	0.15	2.03	4.07	8.14	24.38
Sports	6390	0.22	0.66	0.85	0.78	1.53	3.01	8.51
Entertainment	3450	0.21	0.53	0.69	0.61	1.21	2.43	7.23
Gaming	2080	0.31	0.70	0.95	0.47	0.95	1.90	5.67
Technology	5912	0.06	0.43	0.66	0.28	0.57	1.13	3.41
Crypto	1267	0.38	0.77	0.87	0.23	0.45	0.90	2.60
Science	3561	0.10	0.37	0.49	0.10	0.20	0.41	1.20
Business	1632	0.08	0.27	0.38	0.05	0.09	0.19	0.58

Note: Summary statistics for the communities included in the study. Each row represents a category of news. The Number of Snapshots column contains the number of Wayback Machine snapshots for all communities in each category. The columns labeled Share of Posts Missing denote the share of submissions that lack information on publisher domain, slant score, and credibility rating. The columns labeled Number of Comments show the average number of comments a submission receives in the 5, 10, 20, and 60 minute periods following a snapshot. These columns average over both periods (i.e. snapshots) and positions in the feed.

et al., 2020]. For each comment in the data, this model constructs a set of scores for predicted sentiment and emotion.

I focus on comment sentiment as the primary quality measure of a comment's text. Appendix Figure A.1 shows the correlation between text sentiment, predicted toxicity, and the comment's emotional content. Negative-sentiment comments are more likely to be classified as toxic, more likely to contain strong negative emotions such as disgust and anger, and less likely to exhibit joy. Moreover, inspection reveals comments labeled as negative by the Pérez et al. [2021] model are often extremely vulgar and unlikely to contribute productively to the discussion.

3 Estimating Position Effects

In this section, I estimate the causal effect post rank has on the number of comments the post receives. Recall I ultimately want to understand how engagement-maximizing ranking algorithms impact the type of content to which users are exposed and with which they engage. A key challenge in this analysis is the endogeneity of post rank, where the rank of a post is correlated with its potential outcomes. This section introduces the identification strategy I use to overcome this challenge by estimating position effects – the causal effects of post rank on engagement. This serves three purposes. First, the treatment effect estimates provide important motivation for the analysis, given that I find a post's rank has a large causal effect on engagement, meaning the ranking algorithm plays an important role in shaping the posts with which users eventually engage. Second, I use treatment effect estimates to validate a recommender system approach to personalization in Section 4. Finally, the causal estimates from this section will be utilized directly in identifying the choice model of user engagement that is employed in the counterfactual analysis.

Naive comparisons between posts with lower ranks (higher on the page) and posts with higher ranks (lower on the page) are unlikely to identify the causal effect of rank as I expect potential outcomes to be correlated with post rank [Narayanan and Kalyanam, 2015, Ursu, 2018]. It is likely that posts with high potential outcomes, or latent commentability, are more likely to be shown higher on the page. This dependence would be severed if Reddit ranked posts in random order and the effect of rank on engagement could be identified using the simple comparison [Ursu, 2018]. However, this is rarely the case in observational settings containing ranked content like the one studied here.

Therefore, I exploit a regression discontinuity to identify the causal effect of rank on engagement. Until 2017, Reddit maintained an open-sourced mirror of its code base, which allows me to directly inspect the algorithm used to sort posts [reddit.com, 2017]. The algorithm assigns a ranking score for each post and ranks posts in descending order of these scores. Formally, a post's ranking score is defined as

$$s_{jt} = \text{sign}\left(u_{jt}\right)\log_{10}\left(\max\left\{\left|u_{jt}\right|, 1\right\}\right) - \frac{a_{jt}}{45,000} \tag{1}$$

where u_{jt} is the net number of upvotes minus downvotes that post j had at time t and a_{jt} is the age of the post in seconds.[9] This requires that for the ranking score of a post with a positive vote score to remain constant, every 12.5 hours the net number of upvotes minus downvotes must increase by a factor of 10 to offset the age penalty. Importantly, this defines a continuous score that determines post rank, creating a regression discontinuity that can be used to identify position effects [Narayanan and Kalyanam, 2015].

To give a concrete example of the regression discontinuity I exploit, consider two adjacent posts i, j with ranking scores s_i, s_j and observed ranks r_i, r_j. There is a discontinuous jump in the probability of post i being ranked lower than post j when the continuous forcing variable $s_i - s_j$ crosses zero. I take advantage of this discontinuity to identify the effect of rank on future engagement, under the assumption that potential outcomes (i.e. latent post quality) are continuous across the zero threshold of the forcing variable $(s_i - s_j)$.

3.1 Implementation Details of the Regression Discontinuity Design

I now discuss the implementation details of the regression discontinuity used to estimate the causal effect of post rank on future engagement. In particular, I focus on estimating the causal effect of moving up from position $r+1$ to position r on the feed. To simplify notation, let D_i be a treatment indicator (i.e. $D_i = 1[s_i > s_{-i}]$), and the forcing variable is denoted $\Delta s_i = s_i - s_{-i}$.

A feature of this setting is that the running variable is a composition of two scores, the ages and vote scores of the posts. This creates a cutoff frontier, shown in Appendix Figure B.6, analogous to geographic regression discontinuity designs. I take advantage of the multiple score nature of the problem and estimate the treatment effect at the origin, which ensures that posts are balanced on both post age and vote score, as described in Cattaneo et al. [2023].

The primary results use a local-linear approximation to the conditional expectation functions on either side of the discontinuity and a uniform kernel. I will show the estimates are similar under alternative specifications. I restrict to observations within a bandwidth λ of the cutoff chosen to minimize the mean squared error of the treatment effect estimator [Calonico et al., 2014, Cattaneo et al., 2020] and demonstrate the results are not sensitive to this choice (Appendix B.2).

For each of the 24 positions on the first page of the feed, I estimate the treatment effect of moving from position $r+1$ to position r as

$$\hat{\tau}_r = \hat{\mu}_r^+ - \hat{\mu}_r^- \tag{2}$$

[9] I normalize the post's timestamp by the period to interpret the second term as age. This is equivalent to adding a constant to all posts in a period and does not affect the ranking, but does make the ranking score more interpretable.

where $\hat{\mu}_r^+$ is the estimated intercept from the local linear regression to the right of the discontinuity and $\hat{\mu}_r^-$ is the intercept to the left of the discontinuity [Cattaneo et al., 2020]. I estimate the treatment effect separately for each position in the feed, allowing the treatment effect of being promoted from position $r+1$ to position r to vary by position. In Table 2 and Appendix B.2, I show the results are not sensitive to the degree of polynomial approximation or the choice of kernel. Following best practices [Cattaneo et al., 2020], statistical inference uses robust bias-corrected standard errors that are clustered at the period level.

3.1.1 Measurement Error in the Running Variable

A challenge in this setting is that the running variable is constructed using data scraped from the Internet Archive's WayBack Machine and the reconstructed ranking scores do not completely determine the rank of a post. This is a result of several factors. First, Reddit explicitly adds noise to the vote scores shown to users to combat vote manipulation [Muchnik et al., 2013].[10] Second, Reddit caches votes and rankings for performance purposes due to the large amount of traffic the platform receives.[11] Caching means the ranking score and actual ranks are not continuously updated. This makes it possible for the observed ranks to differ from what is implied by the relative ranking scores as either the scores or observed rankings are a cached version.

Adding noise to the vote score introduces measurement error into the running variable and can bias traditional regression discontinuity estimates. To estimate the local average treatment effect of rank in the presence of measurement error in the running variable I follow Dong and Kolesár [2021] by excluding posts within a doughnut around the discontinuity. I manually select a doughnut width of 0.05 on either side of the cutoff and show in Appendix B.2 that the results are robust to the choice of doughnut width. Under the assumption that the doughnut excludes all periods where the posts are misclassified due to measurement error, Dong and Kolesár [2021] show that the usual regression discontinuity estimators identify a local average treatment effect.

After excluding posts within a doughnut of the discontinuity, I assume the remaining mismatch between post rank and the relative ranking scores is not due to measurement error. This assumption appears justified, as the probability of mismatch is constant as one moves away from the discontinuity (Figure B.2). If this were driven by the noise added to vote scores, the probability of mismatch would decline further away from the discontinuity as the probability the noise added is sufficiently large to misclassify the posts declines. Therefore, estimating the local average treatment effects using local linear regression results in conservative estimates of position effects.

[10] https://www.reddit.com/wiki/faq

[11] https://web.archive.org/web/20170121192832/https://redditblog.com/2017/1/17/caching-at-reddit/

3.2 Testing the Validity of the Regression Discontinuity Design

I now show evidence that Reddit ranks posts according to the algorithm I describe to establish a first stage in the regression discontinuity analysis. For each position on the feed $r \in \{1, \ldots, 24\}$, I consider the two posts ranked in position r and $r + 1$ and plot the probability that a post is in position r against the running variable (the difference in ranking scores of the two competing posts). Figure 3a shows the discontinuity between position 1 and position 2; the plots for the remaining positions are shown in Appendix B.1. There is a clear discontinuity in the probability of being ranked lower when a post's ranking score surpasses the competing post's ranking score in a period.

In addition, to test that post observables are balanced across the discontinuity, Figure B.11 plots the estimated treatment effect of rank on pre-treatment covariates including publisher slant, publisher credibility, post vote score, and post age. Nearly all estimates are insignificant at the 5% level, suggesting post observables are balanced across the discontinuity. While it is not possible to test the identifying assumption that potential outcomes are continuous through the discontinuity, this result is consistent with such an assumption holding. Appendix B.2.2 presents plots of the non-parametric conditional expectation functions of these covariates around the discontinuity.

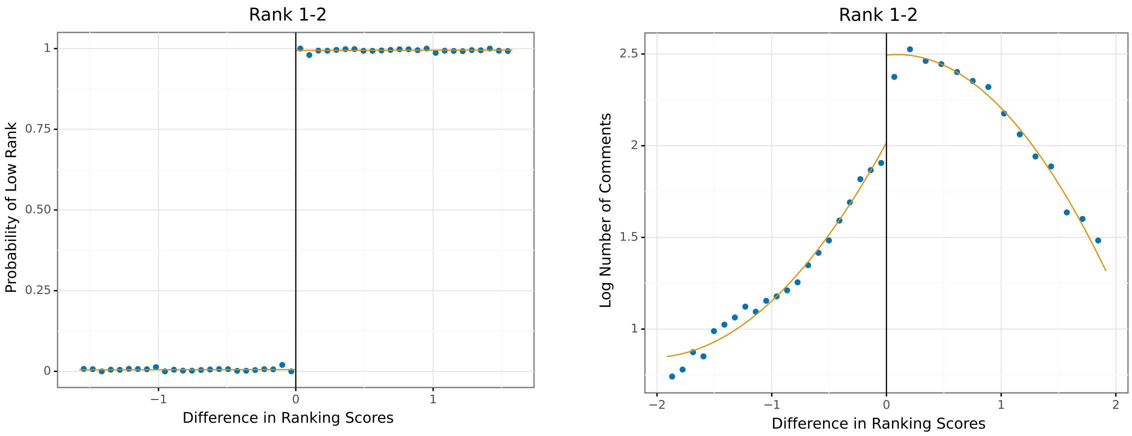
3.3 Position Effect Estimates

I now turn to estimating how post rank affects the engagement a post receives in the window following the snapshot. Figure 3b plots a binned scatter plot of the log of one plus the number of comments a post receives in the 20 minutes following the snapshot against the running variable (Δs_i) to visualize the discontinuity in the outcome variable. There is a clear discontinuity in engagement when a post is promoted to position 1 from position 2. Appendix B.1 shows the same plots for the remaining positions on the feed and the discontinuity in engagement quickly disappears further down the feed, suggesting treatment effects of rank are largest at the top of the feed.

I estimate the local average treatment effect using local linear regression, and present treatment effect estimates in Table 2, which shows the effect of moving from rank $r + 1$ to rank r on the log of one plus the number of comments a post receives in the 20 minutes following a snapshot. Being promoted to the first position has a large effect, with the treatment effect estimate suggesting a 43.6% increase in the number of comments received relative to the second post. The importance of rank quickly dissipates further down the feed. Table 2 also shows the results are robust to the polynomial choice and choice of kernel. Table 2 includes naive OLS estimates of position effects. As expected, OLS substantially overestimates the effect of position on engagement, and this is particularly severe towards the top of the feed.

These treatment effect estimates demonstrate that the ranking algorithm has an important effect in determining the posts with which users engage. This in turn motivates further investigation of what content is promoted when rankings are designed to optimize for engagement, since the platform

Figure 3: Regression Discontinuity Plots



(a) Effect on Post Rank

(b) Effect on Engagement

Note: Regression discontinuity plots for the discontinuity around being promoted to the top position on the feed from the second position on the feed. Here, the x-axis is the running variable – the difference in post ranking scores – and y-axis is (a) the probability a post is ranked lower on the page and (b) the log number of comments received in the 20 minutes following a snapshot plus one. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. Fourth order polynomial fits are plotted alongside the binned mean values. The corresponding figures for the remaining positions on the feed are shown in Appendix B.1.

has substantial power in determining what content users are exposed to and ultimately engage with.

Table 2: Position Effect Estimates

		Regression Discontinuity		
Rank	OLS	Local Linear	Local Constant	Triangular Kernel
1	0.892	0.362	0.217	0.365
	(0.012)	(0.139)	(0.311)	(0.160)
2	0.245	0.240	0.210	0.239
	(0.010)	(0.046)	(0.094)	(0.051)
3	0.146	0.169	0.169	0.146
	(0.009)	(0.040)	(0.083)	(0.045)
4	0.096	0.122	0.136	0.111
	(0.009)	(0.032)	(0.065)	(0.035)
5	0.071	0.114	0.130	0.112
	(0.009)	(0.030)	(0.062)	(0.034)
6	0.071	0.107	0.122	0.113
	(0.008)	(0.029)	(0.060)	(0.032)
7	0.053	0.088	0.106	0.079
	(0.008)	(0.028)	(0.058)	(0.031)
8	0.041	0.081	0.099	0.063
	(0.008)	(0.036)	(0.076)	(0.040)
9	0.041	0.035	0.024	0.033
	(0.007)	(0.025)	(0.050)	(0.027)
10	0.038	0.074	0.094	0.071
	(0.007)	(0.026)	(0.055)	(0.029)
11	0.039	0.052	0.070	0.054
	(0.007)	(0.026)	(0.055)	(0.029)
12	0.017	0.047	0.072	0.045
	(0.007)	(0.023)	(0.047)	(0.025)

Note: Estimates of the local average treatment effect from a post moving from position $r + 1$ to position r on the feed on the log of the number of comments a post receives plus one. Robust bias-corrected standard errors that allow for misspecification of the conditional expectation function and that are clustered at the period level are shown in parentheses. Estimates exclude posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. The bandwidths for each rank are not varied across the various regression discontinuity specifications to isolate the difference due to the different specifications. The corresponding table for positions 13-24 is shown in Appendix B.1.

4 A Recommender System Approach to Personalization

In this section, I study the types of content that are promoted when personalizing the ranking algorithm to maximizing engagement using a reduced form approach. To explore this, I train a collaborative-filtering based recommender system using the matrix of user-level comment counts by publishers. The recommender system then recommends publishers on which a user is most likely to comment in a period. I validate this recommender system by estimating heterogeneous treatment effects when the regression discontinuity experiments align with the recommender system's predictions. I find that the recommender system effectively predicts treatment effects, a result that suggests the model has learned important aspects of user preferences. I then study the types of content that gets promoted under this simple recommender system to understand the extent to which personalized engagement maximization impacts individual news diets.

The primary purpose of this section is to provide reduced-form evidence that personalizing content to maximize engagement promotes low-quality content to a subset of users and lowers the diversity of publishers that are promoted. This approach has two advantages over the discrete choice model and counterfactual analysis I study in Section 5 and Section 6. First, this model is trained using comment decisions from over 500,000 users and is evaluated on comment decisions of over 180,000 users. This is a much larger sample than that used in the choice model approach, as I can use comment decisions on articles during periods not captured in Wayback Machine snapshots during the training process. I find consistent results across both approaches, which gives confidence that the findings of the choice model approach can be generalized to a broader set of users. Second, I can evaluate this simple approach by predicting treatment effects to give confidence that the model has learned important aspects of preferences.

4.1 Training and Validating the Recommender System

To train the recommender system, I split user-level comment data into training and test sets. The test set consists of comments on articles that appear in Wayback Machine snapshots and the training set consists of comments on articles that do not appear in Wayback Machine snapshots. The test set is used to evaluate the recommendations through heterogeneous treatment effects. I focus this analysis on the politics community because of its importance to managers, policy makers, and users. In the training set, I generate a matrix of user comment counts by publisher domain, where each row represents a user and each column a publisher. I use this matrix to train a collaborative filtering model for implicit data, following Hu et al. [2008]. This simple model assumes that user preferences for a publisher can be represented by the dot product of low-rank vectors of latent user and publisher features. Appendix B.3 shows the publisher embeddings learned by the model are correlated with observable features. More specifically, publisher popularity and slant are the observable publisher features most correlated with the latent embeddings. Given the publisher and user features, the recommender system then recommends publishers that a user is more likely to prefer.

To evaluate the recommender system, I estimate heterogeneous treatment effects comparing periods when the model predicts a user's preferred publisher was promoted to the top of the feed in the regression discontinuity experiments relative to when the non-preferred publisher was promoted. For each period and user, I determine if the preferred post of a user is promoted, the preferred post is demoted, or the user is indifferent. A user is indifferent in a period if the two publishers are within 1 percentile of one another in the model's recommendations for that user. The preferred publisher is promoted for a user in a period if the publisher of the first post is at least 1 percentile higher than the publisher of the second post in the model's recommendations for the user. Likewise, the preferred publisher is demoted if the publisher of the first post is at least 1 percentile lower than the publisher of the second post. I then sum the total number of comments for each post and period across users based on whether the user-period is classified as the preferred post being promoted, demoted, or indifferent. Finally, I estimate the regression discontinuity heterogeneous treatment effects through local linear regression. Given the reduced power in identifying heterogeneous treatment effects, I inflate the bandwidth used in Section 3.3 by a factor of two and use cluster robust standard errors rather than standard errors that are robust to misspecification of the conditional expectation function.[12]

Heterogeneous treatment effect estimates are shown in Table 3 and suggest that the recommender system effectively predicts treatment effects for the top position in the feed. The treatment effect is substantially – 13 percentage points – larger when a user's preferred publisher is promoted versus when the user's preferred publisher is demoted. That the recommender system is able to predict treatment effects confirms that the recommender system has learned important aspects of user preferences.

4.2 Recommender System Results

I now turn to summarizing the properties of the recommender system to understand the types of content promoted when personalizing rankings and to motivate the choice model presented in Section 5. For each user-period, I determine the most preferred publisher according to the recommender system and calculate the share of promoted publishers that are classified as highly credible. I also calculate the primary measure of slant diversity, which is the first Wasserstein distance between the share of publishers promoted in each slant partition and the uniform distribution. The distributions of these summaries are shown in Figure 4 alongside the quantity under the existing ranking. The distributions indicate that the majority of users experience improved news diet quality in terms of publisher credibility, though an important minority of users experience a material deterioration in

[12] This assumes that the conditional expectation function is linear within the bandwidth and does not account for misspecification.

Table 3: Validating the Recommender System

	Preferred Promoted	Preferred Demoted	Indifferent
D	0.81	0.68	0.62
	(0.04)	(0.04)	(0.04)
Δs_{jt}	0.66	0.51	0.73
	(0.12)	(0.12)	(0.12)
$\Delta s_{jt} \times D$	-1.05	-0.61	-1.44
	(0.24)	(0.24)	(0.27)
Intercept	2.15	2.15	1.95
	(0.06)	(0.06)	(0.07)
Obs	3556	3556	3556
R^2	0.10	0.08	0.04

Note: This table shows regression discontinuity heterogeneous treatment effect estimates using a local linear regression. Each column presents estimates of the local linear regression of the outcome (log of one plus the number of comments of each type) on an intercept, treatment indicator, running variable, and running variable interacted with the treatment indicator. The first row contains the coefficient on treatment, which is the local average treatment effect of being promoted to the first position on the feed from the second position. The treatment effect is estimated separately depending on whether a user's preferred publisher is promoted (first column), demoted (second column), or the user is indifferent between the publishers (third column) in the given period.

the quality of their news diets. In terms of diversity, a large majority of users are recommended a less diverse set of publishers.

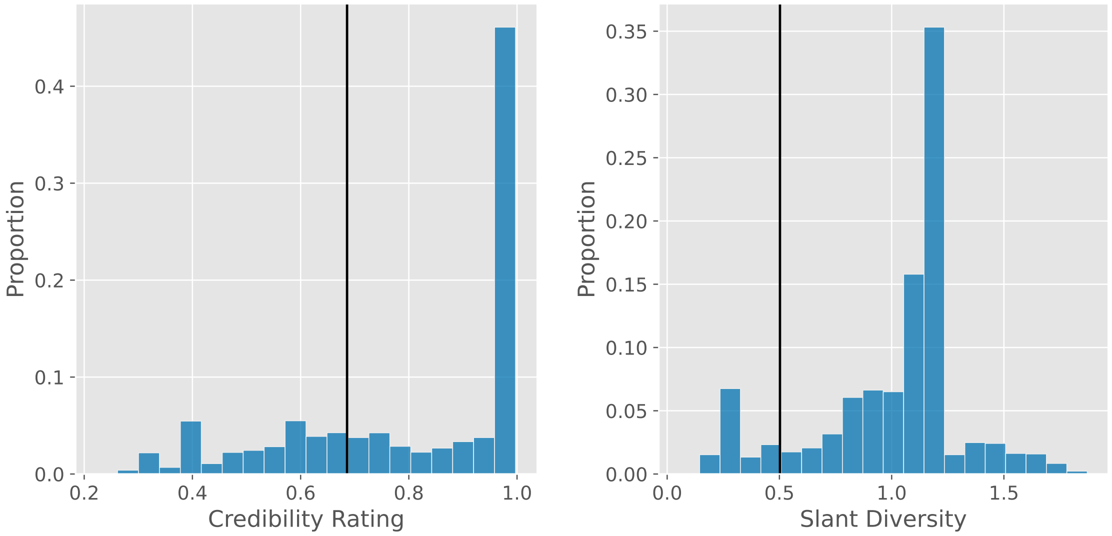
While these results suggest that optimizing for engagement using personalized rankings has a heterogeneous impact on the credibility of publishers that are promoted and a near-uniform decrease in slant diversity, this approach has important limitations. First, the recommender system is trained on observational data without accounting for endogenous post rank [Chaney et al., 2018]. The simple collaborative filtering model trained here also differs substantially from the more advanced models – which often employ deep learning – used in practice (see Zhang et al. [2019] for an overview of current deep learning based approaches to recommendation systems). In addition, this approach does not allow for within-publisher article heterogeneity, wherein certain articles are likely to garner more attention irrespective of the publisher. Finally, this approach is limited to analyzing the type of content promoted rather than modeling the content users eventually engage with under counterfactual rankings. Because it allows me to quantify the counterfactual ranking algorithms' impact on engagement – an outcome that serves as a closer proxy to advertising revenue – modeling engagement is critical to understanding the implications for the platform. The choice model and counterfactual analysis presented in Section 5 and Section 6 address these limitations directly.

Despite these limitations, that this model can accurately predict treatment effects indicates the model has learned useful information about user preferences. Moreover, this model can be

Figure 4: Summary of Promoted Publishers in Recommender System Approach

(a) Publisher Credibility

(b) Slant Diversity



Note: This figure summarizes the user-level distribution of promoted publishers in the recommender system approach to personalization. In each user-period, I find the publisher out of the top 25 posts that the recommender system would promote first. These figures plot the user-level distribution of the high-credibility publisher share and the first Wasserstein distance between the share of promoted publishers from each slant partition and the uniform distribution. The distance is zero when a user is equally likely to be promoted a publisher from each partition of publisher political slant. Higher values of the Wasserstein distance indicate the user is being promoted a less diverse set of publishers. The maximum distance is 2, which would only occurs when a user is promoted entirely publishers from either the extreme left or extreme right publisher partitions.

estimated using data from a larger set of users since engagement on posts not included in the Wayback Machine snapshots can be included in training. This allows the recommender system approach to encompass over 180,000 users while the choice model is estimated on a smaller set of highly active users. As I will argue, the results from both analyses are similar and give confidence that the results generalize to a broader set of users.

5 Model of Individual Engagement Decisions

I now estimate a model of user engagement that allows me to estimate engagement patterns under counterfactual ranking algorithms. Section 5.1 introduces the model of individual decisions, Section 5.2 describes identification and the estimation approach, and Section 5.3 summarizes the model estimates and fit.

5.1 Model

Users indexed by i visit the platform in periods indexed by t and are exposed to a ranked feed of posts indexed by j. In each period, users are exposed to a post in position r_{jt} if $v_{ijt} = 1$, which is an independent Bernoulli random variable equal to one with probability $p\left(r, t\right)$. I use a parsimonious parameterization of the exposure probability, $p\left(r, t\right) = p_t p_r$, where p_t is the probability of accessing the platform in period t and p_r is the probability of being exposed to a post in position r conditional on accessing the platform. If exposed to a post, users receive utility

$$u_{ijt} = \delta_{ijt} + \varepsilon_{ijt} \tag{3}$$

if they comment on post j in period t, which I denote d_{ijt}. Consumers comment if they are exposed to the post and the utility from commenting exceeds the utility from the outside option $\left(u_{i0t}\right)$[13]

$$d_{ijt} = 1\left[v_{ijt} = 1\right] 1\left[u_{ijt} \geq u_{i0t}\right]. \tag{4}$$

I model $\delta_{ijt} = x'_{jt}\left(\bar{\beta} + \beta_i\right) + \xi_{jt} = \delta_{jt} + x'_{jt}\beta_i$ where x_{jt} is a vector of observable article features, $\bar{\beta}$ represents average preferences, β_i is a vector of the deviation of user i's preferences from the mean, and ξ_{jt} is latent article commentability.[14] Post rank is excluded from utility in this model, implying that rank does not impact choice conditional on exposure to a post.[15] Finally, normalize $\delta_{i0t} = 0$ and assume ε_{ijt} is an independent and identically distributed Type 1 Extreme Value preference shock. This results in the mixed logit choice probabilities multiplied by the exposure parameter $p\left(\cdot\right)$.

$$P_{ijt} = P\left(v_{ijt} = 1, u_{ijt} \geq u_{i0t}\right) = p\left(r_{jt}, t\right) \frac{\exp \delta_{ijt}}{1 + \exp \delta_{ijt}} \tag{5}$$

Conditional on commenting on a post, users choose the sentiment of the comment to submit.

[13] A key simplification is the stylized process by which users form consideration sets. A more flexible model that allows users to consider a subset of posts and comment on their most preferred post introduces substantial computational challenges as the number of potential consideration sets grows combinatorially. These models would likely yield similar results given users are highly unlikely to comment on more than one post in either the data or in the counterfactual simulations. Therefore, given the substantial computational benefits of assuming independence between comment decisions, I assume that users make engagement decisions on posts independently. The independence assumption between posts also prohibits preferences that depend on features of other posts on the feed such as a preference for a diverse feed. Experimental evidence from a music recommender system found little evidence of a preference for diversity consistent with the approach taken here [Chen et al., 2023].

[14] The latent commentability term ξ_{jt} is often referred to as latent quality in the literature estimating demand systems. To avoid confusion with publisher credibility, I refer to ξ_{jt} as latent commentability, where this captures a vertical component making all users more likely to comment on the article.

[15] This assumption is motivated by the findings of Ursu [2018] that demonstrates empirically that rankings impact search probabilities but, conditional on search, do not affect purchase probabilities in an online travel platform. This is also consistent with recent work modeling personalized rankings in e-commerce [Donnelly et al., 2023]

Users can either submit a comment with negative sentiment or neutral sentiment. Users choose the probability with which their comment will be perceived negatively based on the user-specific and vertical components of comment utility. That is, conditional on commenting users choose the probability that comment ijt will be a negative comment as follows

$$\log \frac{b_{ijt}}{1-b_{ijt}} = \beta^s_{i0} + \beta^s_{i1}\left(\delta_{ijt} - \xi_{jt}\right) + \beta^s_{i2}\xi_{jt} + \varepsilon^s_{ijt} \tag{6}$$

where b_{ijt} is the probability user i's comment on post jt is a negative comment, $\delta_{ijt} - \xi_{jt}$ is the user-specific component of comment utility user i receives when commenting on post jt, ξ_{jt} is the vertical commentability component of post jt, and $\beta^s_i = \langle \beta^s_{i0}, \beta^s_{i1}, \beta^s_{i2} \rangle$ is a vector of individual i's sentiment preferences.

5.2 Identification and Estimation

5.2.1 Identification of Model Parameters

The key identification challenge in this model is that observed post ranks are correlated with latent commentability, or $E\left[\xi_{jt} r_{jt}\right] \neq 0$. I now describe how this model is identified using the regression discontinuity from Section 3 and user-level engagement decisions.

I first describe how the exposure parameters $(p_t,\, p_r)$ are identified. I assume that each user logs on to the platform with probability p_t, independent of article features or preference shocks. This probability is identified via the share of users who visit the platform in each period which I estimate using data on the number of users online during each period. Conditional on accessing the platform, I assume all users are exposed to the top post on the feed implying that $p_1 = 1$.[16] The remaining exposure parameters p_r are identified by the reduced form treatment effects after I impose constant treatment effects[17]

$$\tau_r = \log \frac{E\left[d_{ijt}(r)\right]}{E\left[d_{ijt}(r+1)\right]} = \log \frac{p_r}{p_{r+1}}. \tag{7}$$

The assumption of constant treatment effects could in principle be relaxed to allow for arbitrary individual heterogeneity and heterogeneity along observed article features, though the demands on the data grow substantially if this type of heterogeneity are included. For example, allowing for individual heterogeneity would require estimating the reduced form treatment effects separately for each user.

Given exposure parameters, individual preference parameters and mean preference parameters are identified from the assumption that article features are exogenous $E\left[x_{jt}\varepsilon_{ijt}\right] = 0$ and $E\left[x_{jt}\xi_{jt}\right] =$

[16] The results are robust to other choices of p_1 as shown in Appendix Section C.4.

[17] That is, I assume $E\left[Y_{jt}(1)\right] = e^{\tau_r} E\left[Y_{jt}(0)\right]$ where $Y_{jt}(D)$ is the potential outcome under treatment D for the number of comments post j in period t received following a snapshot.

0. Finally, the parameters in the sentiment model are identified by the assumption that ε_{ijt}^s is mean-independent of ε_{ijt}, ξ_{jt}, and x_{jt}.

5.2.2 Estimation

I again estimate the choice model using data from the politics community given the relevance of this community to managers, policy makers, and users. I use individual-level comment decisions and restrict the sample to users who comment on at least 25 articles in the periods I study, where a period consists of the 60 minutes following a Wayback Machine snapshot. I will show the results are similar to the reduced form recommender system findings that use a larger and more representative sample, thereby providing confidence that the results generalize to a broader set of users. Nonetheless, this sample of highly active users is also of direct interest to the platform because user-generated content is vital to platform's business model.

I take this model to the data using a two step procedure that simplifies the computation given the large number of periods, users, and posts. In the first step, I estimate the exposure parameters p_t and p_r. I estimate p_t by combining data on the number of users online at the start of each period, which are observed in the Wayback Machine snapshots, with the platform's public statements on the average session duration to estimate the number of users who log on to the platform during each period using Little's law [Little, 1961]. I then use public usage statistics again to estimate the number of active community members and calculate the share of active community members who log on in each period. Finally, I smooth estimates of p_t by taking the fitted values of a regression of the raw values of p_t on quarter and day of week fixed effects. The full details of this process are described in Appendix C.3. I then estimate the remaining exposure parameters using an empirical analog of Equation 7 ($p_r = \exp\left\{-\sum_{r'>1} \tau_{r'-1}\right\}$).

Second, given the estimates of p_t and p_r I estimate the individual preference parameters β_i using maximum likelihood

$$\mathcal{L} = \sum_t \sum_i \sum_j d_{ijt} \log P_{ijt} + (1 - d_{ijt}) \log (1 - P_{ijt}) \,. \tag{8}$$

Finding the maximum likelihood estimate involves solving a high-dimensional optimization procedure due to the large number of individuals and posts. Therefore, I use the following iterative algorithm. First, I initialize a guess of ξ_{jt} and, conditional on these unobserved commentability parameters, estimate the individual-level preference parameters using maximum likelihood. I then invert observed engagement shares [Berry, 1994] using the Berry et al. [1995] contraction mapping to find the values of ξ_{jt} such that predicted market shares equal observed market shares.[18] I iterate between these two steps until convergence. Splitting the estimation algorithm into these two steps

[18] There are instances in the data where a post receives zero comments. I assume that ξ_{jt} is bounded below such that the minimum predicted market share is equal to 0.01% in these situations.

allows the maximum likelihood parameters to be estimated in parallel vastly reducing the required computation. Inference on the preference parameters uses cluster-robust standard errors.

The preference estimates of any individual user will contain substantial sampling error given the limited number of periods and comment decisions. This implies that the distribution of preference estimates will be a convolution of the true distribution of preferences and sampling error, leading the distribution of estimates to be over-dispersed relative to the true distribution. To correct for this over dispersion, I shrink all preference estimates towards the grand-mean using the empirical Bayes procedure described in Appendix C.2.

5.3 Model Estimates

To assess the fit of the model, Table 4 presents summary statistics of actual engagement and engagement predicted by the model. The distribution of actual engagement with engagement predicted by the model is also shown graphically in Figure C.17. Figure C.17a demonstrates the correlation between actual user engagement and predicted user engagement. The correlation is high, though the model tends to overestimate total engagement for users with the highest engagement. Figure C.17b shows the correlation between actual and predicted user engagement by publisher credibility and the model again has a high correlation between actual and predicted engagement by group.

Table 6a summarizes the distribution of individual preference estimates $(\bar{\beta} + \beta_i)$. It is helpful to summarize preferences for publisher slant through each user's bliss point, which is defined as the slant the user most prefers

$$b_i^* = \begin{cases} \text{sign}\left(\beta_{is}\right) & \text{if } \beta_{is^2} \geq 0 \\ \min\left\{1, \max\left\{-1, -\frac{\beta_{is}}{2\beta_{is^2}}\right\}\right\} & \text{if } \beta_{is^2} < 0 \end{cases} \tag{9}$$

where β_{is} (β_{is^2}) is user i's taste parameter on post slant (slant squared). The marginal distribution of slant bliss points is shown in Figure 5. It is evident there is substantial heterogeneity within preferences in the politics community. Just over half of users prefer more credible publishers, while the remaining users prefer less credible publishers. Regarding political slant, there is also substantial heterogeneity, with a large mass of users preferring outlets slightly left of center. There are also mass points at each political extreme, with nearly 20% of users preferring outlets that are strongly left leaning and over 25% of users preferring outlets that are strongly right leaning.

Table 6b summarizes the estimates of individual-level preferences to submit a negative comment based on the vertical- and individual-specific components of comment utility (Equation 6). There is substantial heterogeneity in user preferences to submit a negative comment with 51.6% of users more likely to comment negatively on posts in which they are more likely to comment. Figure C.18 reveals this is especially true for users more likely to comment on left-leaning posts (i.e. they have a negative bliss point) and users who prefer to comment on less credible publishers. Ranking algorithms that optimize solely for engagement will increase the share of negative posts for these users.

Table 4: Summary of Model Fit

		Actual		Model	
		Mean	Std	Mean	Std
Total		52.39	38.85	54.04	35.27
Credibility	High	43.54	32.19	42.71	27.86
	Low	8.85	8.17	11.33	8.25
Slant Partition	Strongly Left	13.38	11.86	14.04	10.40
	Left	7.99	6.75	8.14	5.30
	Middle	13.49	10.63	13.68	8.90
	Right	13.58	10.75	13.88	9.11
	Strongly Right	3.95	3.87	4.31	3.32

Note: Summary statistics of the choice model fit. The Actual columns report the average and standard deviation of the total number of comments posted by each user and the number of comments by publisher rating. The Model columns report the model's predicted values for the same quantities under the existing ranking algorithm.

6 Counterfactual Ranking Algorithms

6.1 Background on Engagement Based Feeds

While it is beyond the scope of this article to provide a comprehensive review of the architectures and implementations of news feed algorithms deployed in practice, I will give a high-level description that abstracts away from many of the low-level platform-specific implementation details. See Thorburn et al. [2022] and Narayanan [2023] for more thorough reviews. At a high level, social media ranking algorithms can typically be decomposed into two primary components: candidate generation and ranking.

In candidate generation, the algorithm usually selects a set of posts that are eligible to be shown to a user. As described in Thorburn et al. [2022], this is often either a computationally efficient algorithm that filters posts based on a user's network – examples include the Facebook News Feed [Lada et al., 2021] and Twitter Timeline [Twitter, 2023] – or a bare bones implementation of the

Table 5: Distribution of Individual Preference Estimates

	Mean	Std	1%	25%	50%	75%	99%
Constant	-4.51	0.75	-6.05	-5.02	-4.58	-4.07	-2.44
Slant Score	-0.20	0.64	-1.60	-0.65	-0.21	0.23	1.27
Slant Score^2	-0.30	0.82	-2.10	-0.88	-0.30	0.26	1.59
Credibility Rating	-0.02	0.86	-2.30	-0.53	0.02	0.55	1.85
ξ_{jt}	0.00	0.93	-2.21	-0.61	0.03	0.60	2.11

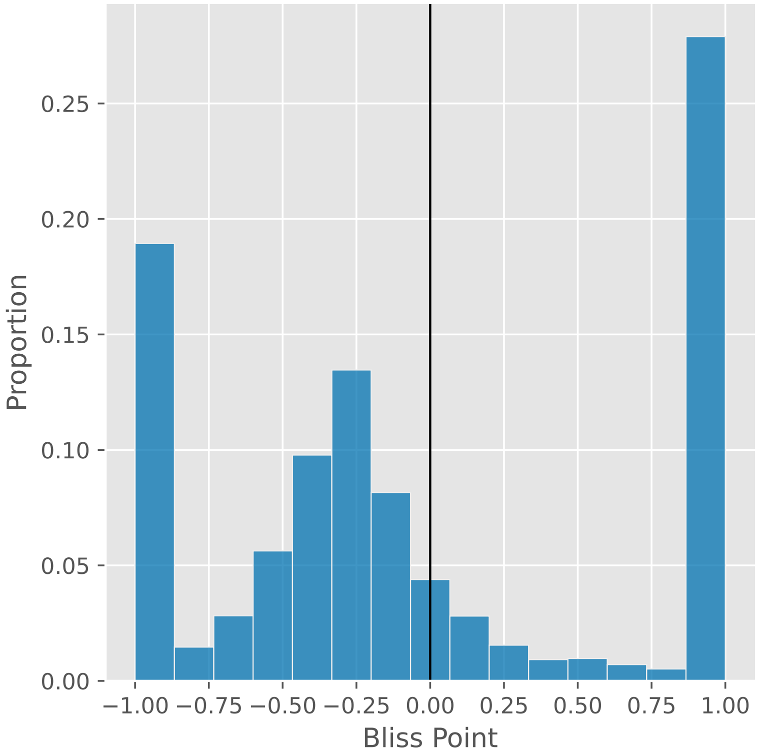
(a) Individual Comment Preference Estimates

	Mean	Std	1%	25%	50%	75%	99%
Intercept	0.20	7.22	-18.39	-3.86	0.20	4.25	18.73
Heterogeneous component	0.04	1.53	-3.94	-0.82	0.06	0.90	3.97
Vertical component	0.03	0.08	-0.19	-0.01	0.03	0.08	0.23

(b) Individual Sentiment Preference Estimates

Note: This table shows the user-level distribution of preference estimates. Panel (a) presents the distribution of comment preferences (Equation 4). The values for Constant, Slant Score, Slant Score^2, and Credibility Rating contain the user-level comment preferences. The values of ξ_{jt} are at the article level and show the distribution of latent article commentability. Panel (b) presents the distribution of sentiment preferences (Equation 6). The heterogeneous component captures how the likelihood of a user to submit a negative comment changes in response to changes in the user-specific component of post comment utility. The vertical component captures how the likelihood of a user to submit a negative comment changes in response to a change in the latent commentability term (ξ_{jt}). All preference parameters are shrunk to the grand mean using empirical Bayes.

Figure 5: Distribution of Slant Bliss Points



Note: This figure plots the marginal distribution of user-level slant bliss points. The bliss point is the slant score for which a user is most likely to comment, all else being equal. A bliss point of -1 implies the user is most likely to comment on left-leaning articles and a bliss point of 1 implies the user is most likely to comment on right-leaning articles.

ranking algorithm, as in the YouTube homepage [Covington et al., 2016]. Candidate generation also generally includes content moderation filters that remove posts deemed ineligible to be promoted.

In the ranking step, platforms typically employ a more complicated model that orders posts based on predicted engagement – often implemented as a weighted average of predicted clicks, time spent, comments, and votes [Thorburn et al., 2022, Lada et al., 2021, Twitter, 2023]. Additional higher-level signals such as predicted survey responses are occasionally included in the ranking objective function as well. Finally, the ranking step often includes a post-processing procedure that adjusts the ranking to avoid, for example, showing users only posts from a single highly engaging account.

6.2 Description of Counterfactual Rankings

In this study, I focus on the implications of different objective functions in the algorithmic ranking step conditional on candidate generation. Therefore, the counterfactuals considered here only re-rank the top 25 posts in each period, which I treat as the set of candidate posts to be ranked. This decision is relatively innocuous for analyzing the impact of optimizing for engagement, as latent post commentability is highly correlated with post rank in the data (Figure C.15). Latent post commentability is an important factor in optimizing for engagement, meaning posts that are not in the top 25 posts would be less likely to be ranked high on the feed even if they were included in the candidate posts.[19]

I assume that the platform has high quality estimates of user preferences given their access to rich user-level behavioral data and therefore assume the platform observes $\hat{\beta}_i$ in the counterfactuals. I assume the platform does not, however, observe latent article commentability (ξ_{jt}) and must estimate this through observable article features. I model the platform's estimates of ξ_{jt} as a supervised learning problem where the platform forms estimates of the true latent article commentability ($\hat{\xi}_{jt}$) based on article observables. I operationalize this using a random forest that predicts ξ_{jt} using observable post features including the stock of total and top-level comments, vote score, post age, publisher slant, and publisher credibility rating. This model performs well in the prediction task as demonstrated in Appendix Figure C.19, where it achieves an R^2 of 0.42. With estimates of article commentability, observed post features, and observed user preferences, the platform can estimate engagement probabilities for each user and article conditional on exposure $\hat{P}_{ijt} = \frac{\exp \hat{\delta}_{ijt}}{1+\exp \hat{\delta}_{ijt}}$ where $\hat{\delta}_{ijt} = x'_{jt}\left(\bar{\beta} + \beta_i\right) + \hat{\xi}_{jt}$.

With predicted engagement probabilities for each user-article, the platform then uses the algorithms described below to re-rank posts according to observable post features and the estimated engagement probabilities. To calculate engagement under a counterfactual algorithm, I calculate engagement probabilities for each post and user by multiplying the exposure probability for the post under the counterfactual ranking with the true estimated engagement probability conditional on exposure.

Non-personalized engagement maximizing: The non-personalized engagement maximizing algorithm solves the following maximization problem

$$r_t^N = \arg\max_{r \in \mathcal{R}} \sum_{j=1}^{J} p\left(r_j, t\right) E\left[\hat{P}_{ijt}\right] \tag{10}$$

where $\mathcal{R}$ is the set of possible rankings, $r = \langle r_1, \ldots, r_J \rangle \in \mathcal{R}$ is a vector of possible article ranks,

[19] This assumption does preclude analyzing simple proposed algorithms such as reverse chronological, as the restricted set of candidate posts excludes the high volume of low-quality posts that are often promoted under a reverse-chronological ranking.

and $\hat{P}_{ijt}$ is the platform's estimate of the probability that user i engages with article j in period t conditional on exposure. It is straightforward to show that when $p(r,t)$ is weakly decreasing in r, the optimal ranking sorts articles in descending order of $E\left[\hat{P}_{ijt}\right]$.[20]

Personalized engagement maximizing: The leading counterfactual considered is personalized engagement maximization. The personalized engagement-maximizing ranking solves

$$r_{it}^{P} = \arg\max_{r \in \mathcal{R}} \sum_{j=1}^{J} p\left(r_j, t\right) \hat{P}_{ijt} \tag{11}$$

which by a similar argument ranks articles in descending order of $\hat{P}_{ijt}$ for each user.

Credibility-aware algorithm: While short-term engagement is often used as a proxy for consumer welfare, a growing literature has emerged to study situations where these measures may differ. This disconnect can arise for rational economic agents [Spence and Owen, 1977] and in models with behavioral biases, including agents with present bias [Kleinberg et al., 2022], dual self models, [Kahneman, 2011, Agan et al., 2023], and digital addiction [Allcott et al., 2022]. Moreover, the platform may want to avoid promoting low-quality publishers for brand-safety purposes or to prevent potential regulatory actions. These factors could lead the platform to consider publisher quality in the ranking objective function. Therefore, I consider credibility-aware algorithm that maximizes an objective function that balances two competing objectives: total engagement and engagement with high credibility publishers

$$\mathcal{S}_{ijt} = E\left[d_{ijt}\right]\left((1-\lambda) + \lambda 1\left[c_{jt} \geq \underline{c}\right]\right) \tag{12}$$

where λ reflects the weight on engagement above a minimum credibility threshold $\underline{c}$. Note that this nests the personalized engagement-maximizing algorithm when $\lambda = 0$ and the credibility-maximizing algorithm when $\lambda = 1$. The credibility-aware algorithm solves

$$r_{it}^{O} = \arg\max_{r \in \mathcal{R}} \sum_{j=1}^{J} \hat{\mathcal{S}}_{ijt} = \arg\max_{r \in \mathcal{R}} \sum_{j=1}^{J} p\left(r_j, t\right)\left((1-\lambda) + \lambda 1\left[c_{jt} \geq \underline{c}\right]\right) \hat{P}_{ijt} \tag{13}$$

and is solved by ranking articles in descending order of $\left((1-\lambda) + \lambda 1\left[c_{jt} \geq \underline{c}\right]\right) \hat{P}_{ijt}$ for each user.

Benchmarks: I compare the engagement patterns under the counterfactual algorithms described above to two benchmark algorithms, the ranking employed by the platform (Actual) and a random

[20] To show this, assume for contradiction there exists an optimal ranking with two posts j and j' such that $r_j < r_{j'}$ and $E\left[\hat{P}_{ijt}\right] < E\left[\hat{P}_{ij't}\right]$. Note that the objective under this ranking is weakly less than the objective if the positions of the two posts are swapped

$$\left(E\left[\hat{P}_{ij't}\right] - E\left[\hat{P}_{ijt}\right]\right)\left(p\left(r_j, t\right) - p\left(r_{j'}, t\right)\right) \geq 0$$

because $p(\cdot)$ is weakly decreasing in r. Therefore, this ranking is not optimal, thus providing a contradiction.

benchmark that randomly shuffles the articles shown on the page for each user (Random).

6.3 Counterfactual Ranking Algorithm Results

Summaries of engagement patterns under the different counterfactual ranking algorithms are shown in Table 6. I now turn to describing the quantity, quality, diveristy, and sentiment of engagement in addition to studying how the various algorithms impact publisher market shares.

6.3.1 Impact on Engagement Quantity

The counterfactual analysis suggests that the algorithm employed by the platform, which prioritizes simplicity and transparency, is far from engagement maximizing. That said, the actual algorithm does substantially increase engagement relative to the random benchmark. As expected, optimizing explicitly for engagement leads to a substantial increase in engagement quantity. Much of the benefit comes from ranking articles according to expected engagement without personalization, which is evidenced by the 20.8% increase in engagement under the non-personalized engagement-maximizing algorithm. Personalizing user feeds increases engagement by 22.8% relative to the existing algorithm, providing a modest increase in engagement relative to the non-personalized engagement-maximizing algorithm. While modest in size, this lift does demonstrate the platform has an incentive to personalize rankings to drive engagement. Optimizing for engagement with high-credibility publishers also leads to a substantial increase in engagement relative to the actual algorithm employed (16.6%), but represents a substantial cost in terms of lost engagement relative to the engagement-maximizing algorithms.

Table 6: Counterfactual Engagement Summaries

	Engagement	Diversity	Max Partition Share	Credibility	Negative Engagement Share
Intercept	54.035	0.279	0.290	0.790	0.512
	(0.386)	(0.001)	(0.000)	(0.001)	(0.002)
Random	-6.175	-0.004	-0.001	-0.001	-0.001
	(0.041)	(0.000)	(0.000)	(0.000)	(0.000)
Non-Personalized	11.214	-0.009	-0.004	0.009	0.002
	(0.067)	(0.000)	(0.000)	(0.000)	(0.000)
Personalized	12.329	0.030	0.022	-0.000	0.002
	(0.077)	(0.001)	(0.000)	(0.000)	(0.000)
Credibility Maximizing	8.996	0.009	0.019	0.110	0.001
	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	41675	41675	41675	41675	41675
R-Squared	0.034	0.033	0.090	0.414	0.000

Note: This table reports estimates of a panel regression of each counterfactual outcome on counterfactual algorithm dummy variables. The intercept is the average quantity under the existing algorithm. (1) Engagement represents the number of articles a user comments on. (2) Diversity represents the first Wasserstein distance of engagement shares across publisher slant partitions from the uniform distribution. Recall distributions closer to uniform will have smaller distances, meaning they represent more diverse engagement. (3) Max partition share represents the max share of engagement in across publisher slant partitions. (4) Credibility represents the share of a users engagement with high-quality publishers. (5) Negative engagement share represents the share of comments that are negative sentiment. Standard errors are clustered at the user level. Bootstrapped standard errors that samples users and re-estimates the model are computationally burdensome and have not yet been pursued.

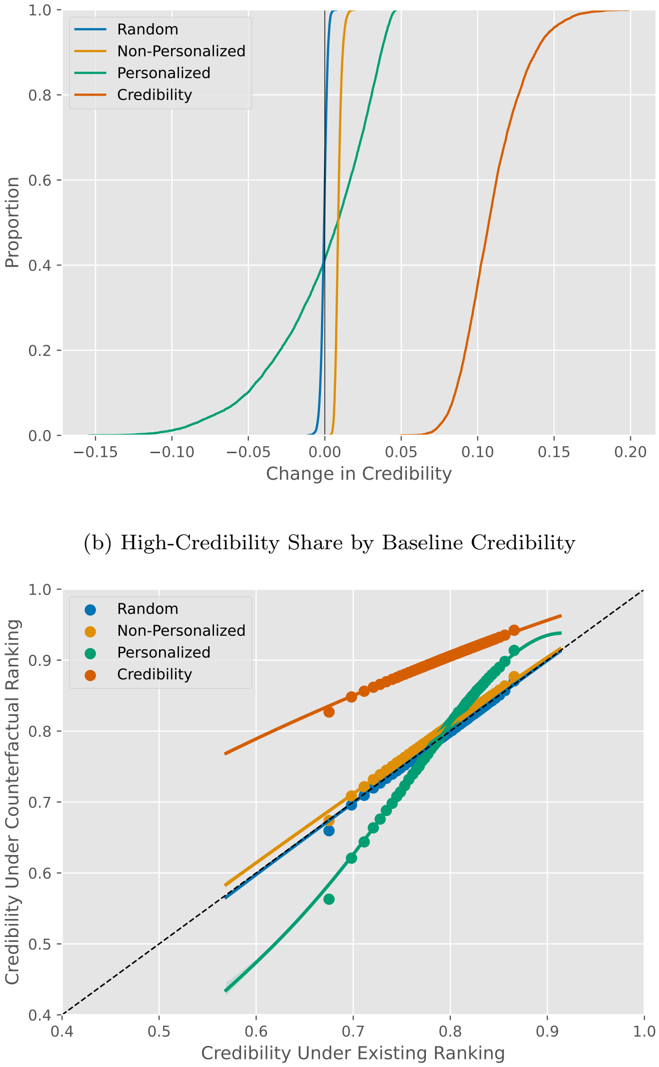
6.3.2 Impact on Publisher Quality

Reddit's algorithm does not materially impact the share of engagement with high-credibility news relative to a random ordering of posts, with both algorithms resulting in 79.0% of the average user's engagement being with high-credibility publishers. Optimizing for engagement also does not lead to a substantial change for the average user, with an average high-credibility engagement share of 79.9% for the non-personalized engagement-maximizing algorithm and 79.0% for the personalized engagement-maximizing algorithm. The credibility-maximizing algorithm does lead to a substantial increase in the share of engagement with high-quality publishers, with the average user's high quality engagement share rising to 90.0%.

Focusing on average changes masks important heterogeneity. Figure 6a plots the empirical CDF of the change in high-credibility shares relative to the existing algorithm. The non-personalized algorithm has little impact on the quality of news diets as the share of engagement with high-quality publishers does not change substantially for any user. The personalized engagement-maximizing algorithm, however, does have substantial impacts for many users despite the negligible average effect. The majority of users experience a modest improvement in the quality of their news diets, as a slightly larger share of their engagement is with high-credibility publishers. However, 41.3% of users experience a deterioration in the quality of their news diets, with a subset of these users seeing the share of their engagement with high quality publishers falling by over 10 percentage points. To better understand what users experience these declines, Figure 6b plots the relationship between news diet quality under the existing algorithm against news diet quality under the counterfactual algorithms. It is clear that users engaging with less credible publishers under Reddit's actual algorithm experience large declines in the quality of their news diets under the personalized engagement-maximizing algorithm. This suggests the algorithm drives a wedge between users along the quality dimension by promoting high-quality publishers to the majority of users who typically engage with high-quality publishers and promoting low-quality publishers to users who have engaged with these publishers in the past. Moreover, the results are robust to the choice of threshold for high-quality publishers (Appendix Section C.4) and I find personalization exacerbates differences between users along the quality dimension even for very low thresholds for high-quality publishers.

Turning to the credibility-maximizing algorithm, I find that optimizing for engagement with high-credibility publishers leads to substantial increases in the share of engagement with credible publishers across all users. Importantly, though, Figure 6b shows that the users experiencing the largest increases are those who engage more with low-credibility publishers under Reddit's actual algorithm. This indicates that including publisher credibility in the objective function narrows the disparity between users with high- and low-quality news diets, a difference that was exacerbated when optimizing only for engagement.

Figure 6: Impact of Algorithm on Share of Engagement with High-Credibility Publishers


(a) Distribution of Change in High-Credibility Share

(b) High-Credibility Share by Baseline Credibility

Note: (a) Plots the empirical CDF of the change in the share of engagement with high credibility publishers under the counterfactual algorithms relative to the existing algorithm. (b) Plots binned mean credibility shares under the counterfactual algorithm against credibility shares under the existing algorithm. Regression line is a fourth-order polynomial fit. Confidence bands represent 95% confidence intervals.

6.3.3 Impact on Engagement Diversity

I now study the impact the counterfactual algorithms have on the diversity of engagement across the political spectrum. To do so, I again calculate the first Wasserstein distance between the share of engagement in each slant partition and the uniform distribution in each of the counterfactual scenarios. The counterfactuals suggest that the random and non-personalized engagement-maximizing algorithms lead to slight increases in engagement diversity relative to the actual algorithm. That said, the personalized algorithm results in a decline in engagement diversity, with the average Wasserstein distance of individual engagement shares relative to a uniform distribution increasing by 10.9%. This increase occurs for a large majority of users, with 71.4% of users experiencing a decline in their engagement diversity in the personalized engagement-maximizing counterfactual. To put this into perspective, under the actual ranking the maximum share of user engagement within a single slant partition averages 29.0%. This rises to 31.2% in the personalized engagement-maximizing algorithm, a relative increase of 7.6%. Turning to the credibility-maximizing algorithm, I also find a decrease in the diversity of engagement as the average distance to uniform engagement shares rose by 3.3% and the average user's share of engagement in their maximal publisher slant partition increased to 30.9%.

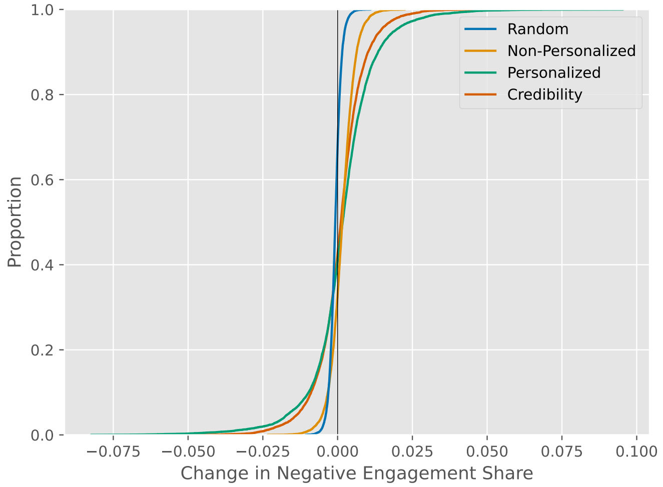
6.3.4 Impact on Discussion Quality

I now turn to studying the impact optimizing for engagement has on discussion quality, as measured through the sentiment of comments submitted to the platform. Table 6 demonstrates that both the non-personalized and personalized algorithms slightly elevate the share of negative-sentiment comments submitted by the average user relative to the existing algorithm. Recall a negative-sentiment comment is significantly more likely to contain strongly negative emotions such as anger and disgust and more likely to be classified as toxic. Moreover, inspecting negative comments reveals they are often extremely vulgar and unlikely to contribute to the discussion in a meaningful way.

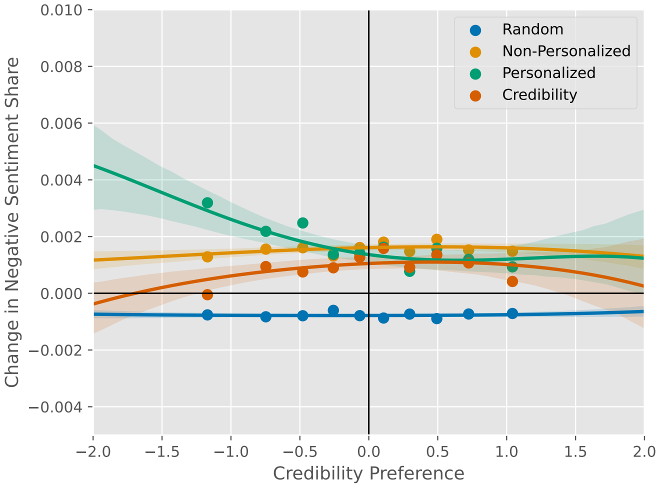
While the effect on the sentiment of the average user is small, personalization increases the variance in sentiment leading to some users commenting more positively while others are shown content that makes them respond negatively (Figure 7a). Figure 7b plots the relationship between the change in the negative-sentiment share of users against user preferences for publisher credibility and I find that users who prefer less-credible publishers have a larger increase in their negative-sentiment share. The same is true of users who prefer left-leaning outlets, consistent with the sentiment preference estimates in Figure C.18.

Figure 7: Impact of Algorithm on Negative-Sentiment Share

(a) Distribution in Change in Negative-Sentiment Share



(b) Change in Negative-Sentiment Share by Credibility Preference



Note: (a) Plots the empirical CDF of the change in the share of users' comments that are negative sentiment under the counterfactual algorithms relative to the existing algorithm. (b) Plots the binned mean in users' change in negative sentiment score against their preferences for publisher credibility. Regression line is a fourth-order polynomial fit. Confidence bands represent 95% confidence intervals.

6.3.5 Impact on Publishers

Thus far, I have focused on the impact that different ranking algorithms have on users and the types of publishers with which they engage. Here, I change the unit of analysis to the publisher and summarize how the counterfactual ranking algorithms impact different types of publishers.

Figure C.20 plots the change in publisher market share by publisher slant (Figure C.20a) and publisher credibility (Figure C.20b).[21] Optimizing solely for engagement leads to a reallocation of market share from left-leaning publishers to right-leaning publishers and a slight increase in the market shares of low-credibility publishers. Optimizing for engagement with high-credibility publishers leads to a reallocation of engagement from politically slanted publishers to more neutral publishers and a reallocation from low- to high-credibility publishers.

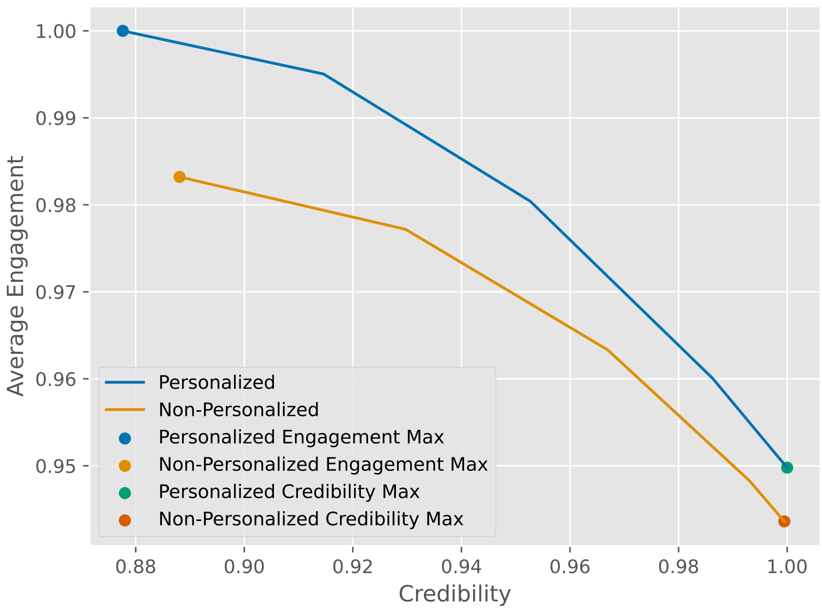
6.3.6 Engagement-Credibility Trade-Off

The results thus far have compared engagement-maximizing algorithms with a credibility-maximizing algorithm. That said, platforms or society may balance these competing objectives in a more nuanced manner rather than preferring either extreme. I now describe the frontier of possible outcomes as λ, the weight placed on engagement with high-credibility publishers, is varied. Figure 8 plots this trade-off along with points corresponding to the total engagement-maximizing algorithm, credibility-maximizing algorithm, non-personalized engagement-maximizing algorithm, and non-personalized credibility-maximizing algorithm. As can be seen, moving to the credibility maximizing algorithm reduces engagement by 5.0%. Nevertheless, platforms can achieve over half of the increase in news diet quality from the credibility-maximizing algorithm for a 2.0% decrease in engagement. This change in engagement is similar in magnitude to the difference between the non-personalized engagement-maximizing algorithm and the personalized engagement-maximizing algorithm. However, the non-personalized algorithm does not meaningfully improve the quality of users' news diets, while the credibility-aware algorithm increases the average share of engagement with high-credibility publishers by 6.8 percentage points for approximately the same total quantity of engagement.

The shape of this frontier is also important, as the gradient is relatively flat around the engagement maximizing algorithms. This suggests that, for small decreases in engagement, the platform can drastically increase the share of engagement with high-quality publishers. However, this also means that small differences in preferences between the platform and society can lead to large discrepancies in outcomes along the credibility dimension – again highlighting the importance of aligning the ranking algorithm's objective function.

[21] Here, publisher market share is defined as a publisher's share of total engagement in the counterfactuals. This differs from how publisher market share would traditionally be defined, and one should think of market share in this context as the share of traffic from the platform.

Figure 8: Engagement-Quality Frontier



Note: This figure plots the frontier of possible outcomes when varying λ in the credibility aware algorithm. The y axis is average total engagement and the x axis is the average share of engagement with high credibility publishers. Both axes are normalized to 1 at their maximal values. Points indicate outcomes under the counterfactual algorithms described in Section 6.2.

6.4 External Validity of Findings

The results in this section are based on a micro-founded model of user engagement decisions. This approach requires a different set of assumptions than the recommender system analysis studied in Section 4 in order to overcome the endogeneity of article position in addition to permitting estimation of engagement shares under counterfactual algorithms. Another benefit of the model-based approach is the ability to study the implications of more nuanced algorithm designs including the credibility-aware ranking algorithm. That said, when the results are comparable between the two approaches they are remarkably consistent. Both approaches suggest that personalization leads to users being exposed to a less diverse set of publishers and exacerbates differences in user exposure with high- versus low-quality publishers. These similarities can help alleviate concerns over selection into the sample of users considered in the choice model, given the recommender system analysis includes over 180,000 users.

7 Discussion and Conclusion

In this study, I evaluate the impact of optimizing for engagement in social media news feed algorithms on the quantity, quality, and diversity of publishers with which users engage. To address this question, I exploit a regression discontinuity design revealed in the platform's code to identify the causal effect of rank on engagement and use these causal estimates to identify a model of user engagement. Using this model, I estimate engagement patterns under counterfactual ranking algorithms including personalized and non-personalized engagement-maximizing and a credibility-aware algorithm that explicitly trades-off total engagement and engagement with high-quality publishers.

The counterfactual analysis demonstrates that social media platforms have a strong incentive to optimize their ranking algorithms for engagement. Optimizing for engagement leads to a dramatic increase in the quantity of engagement and much of this results from promoting posts with which all users are likely to engage. The marginal benefit of personalizing feeds is modest in terms of engagement quantity but has substantial impacts on the credibility and diversity of publishers with which users engage. In particular, personalized engagement maximization drives a wedge between users along the quality dimension. That is, the personalized engagement-maximizing ranking expands the difference in the share of high-quality engagement between users engaging with lower-credibility publishers and those engaging with higher-credibility publishers under the existing algorithm. In addition, personalization nearly uniformly decreases the diversity of publishers with which users engage.

Advertiser concerns about brand safety give platform managers a direct motive to promote credible publishers. Many advertisers seek to avoid advertising on platforms that promote content that is inconsistent with their values or that would create backlash from their consumers. For example, the #StopHateForProfit movement led over 1,000 large advertisers to halt or reduce advertising on Facebook to pressure the platform to expand its efforts to combat hate speech and misinformation [Hsu and Friedman, 2020, Hsu and Lutz, 2020]. There is also evidence suggesting that firms advertising on platforms alongside misinformation often experience customer backlash [Ahmad et al., 2023]. The credibility-aware algorithm demonstrates one method managers can use to improve the quality of content that is promoted on their platforms. The gradient of the engagement-credibility frontier indicates that moving away from the engagement-maximizing algorithm and towards the credibility-maximizing algorithm incurs a relatively small cost in terms of lost engagement. However, this also implies that small differences in the preferences of the platform and society can generate large changes in the amount of engagement with low-credibility publishers despite reasonably small changes to total engagement.

These results also have implications for regulating digital platforms. A growing regulatory trend is to require or incentivize platforms to allow users to opt-out of personalized recommendations or feeds. Examples include the European Union's Digital Services Act or proposed legislation (such as the Filter Bubble Transparency Act, Justice Against Malicious Algorithms Act, and the Protecting Americans from Dangerous Algorithms Act) in the United States. The findings presented here suggest the emphasis on allowing users to opt out of personalization may be misguided. Rather, as the results show, personalization has substantial benefits when the objective function aligns with social preferences. Recall that for approximately the same level of engagement as the non-personalized engagement-maximizing algorithm, the credibility-aware algorithm can increase the share of the average user's engagement with high-credibility publishers by 6.8 percentage points. To the extent that the platform's objective function differs from user preferences or those of society, a more efficient path forward would allow users to adjust the ranking objective function to align with their preferences or regulations that incentivize platforms to place the socially optimal weight on credibility.

Finally, these results are also relevant for publishers and the incentives they face when advertising revenue on traffic originating from social media referrals comprises an important component of their income. I find that personalized engagement maximization benefits publishers with a strong conservative slant and those producing low-quality journalism. This introduces an incentive for publishers to change their coverage to match the increased demand for politically slanted and low-quality journalism.

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Appendix

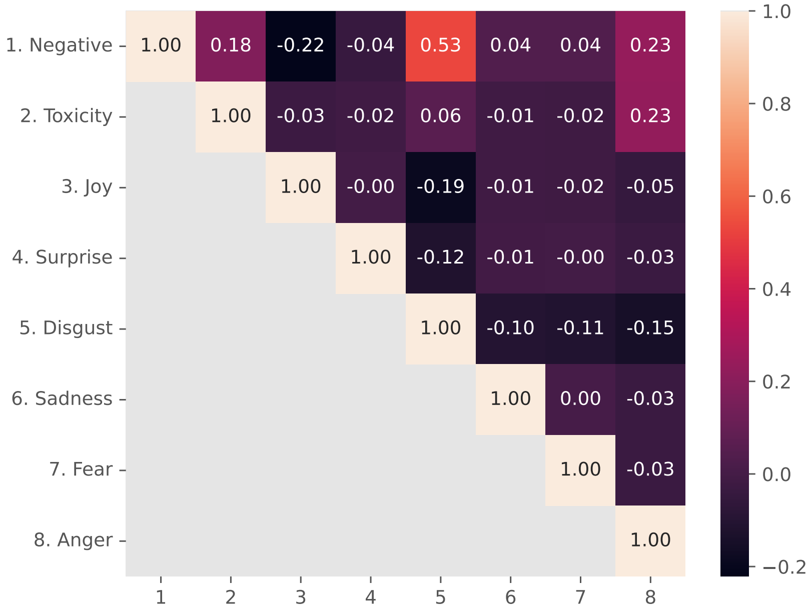
A Data Appendix

Table A.1: Summary of Publisher Ratings

	Slant Score	Credibility
msnbc.com	-0.62	0.59
huffpost.com	-0.31	0.57
nytimes.com	-0.26	0.86
wsj.com	0.01	0.80
foxnews.com	0.61	0.53
breitbart.com	0.74	0.30

Note: Publisher slant and credibility ratings for six widely known publishers.

Figure A.1: Correlation Matrix of Text Features



Note: This figure plots the correlation matrix of comment text features. Negative corresponds to negative sentiment, Toxicity corresponds to the predicted toxicity of the comment, while the remaining 6 features correspond to the emotional content of the post.

B Reduced Form Appendix

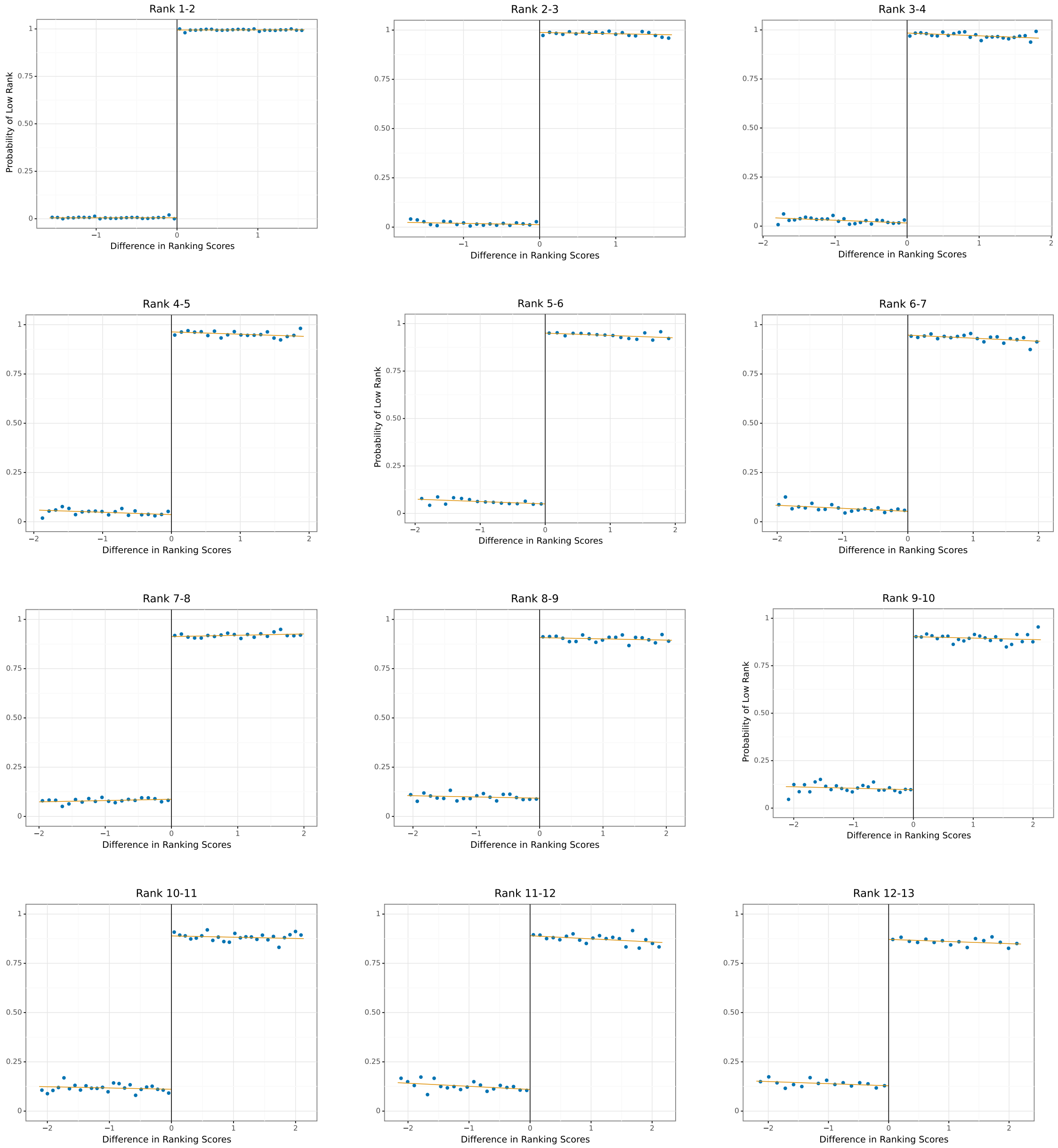
B.1 Additional Figures and Tables

Table B.2: Position Effect Estimates

		Regression Discontinuity		
Rank	OLS	Local Linear	Local Constant	Triangular Kernel
13	0.021	0.021	0.015	0.025
	(0.007)	(0.023)	(0.046)	(0.025)
14	0.036	0.045	0.049	0.038
	(0.006)	(0.023)	(0.047)	(0.025)
15	0.021	0.040	0.067	0.041
	(0.006)	(0.020)	(0.041)	(0.022)
16	0.024	0.033	0.038	0.032
	(0.006)	(0.020)	(0.040)	(0.022)
17	0.015	0.021	0.050	0.017
	(0.006)	(0.022)	(0.045)	(0.024)
18	0.014	0.016	0.018	0.023
	(0.006)	(0.021)	(0.045)	(0.024)
19	0.021	0.002	-0.016	0.012
	(0.005)	(0.020)	(0.042)	(0.022)
20	-0.001	-0.032	-0.074	-0.038
	(0.005)	(0.018)	(0.038)	(0.020)
21	0.020	0.025	0.025	0.020
	(0.005)	(0.018)	(0.036)	(0.020)
22	-0.004	-0.021	-0.035	-0.021
	(0.005)	(0.018)	(0.039)	(0.020)
23	0.009	0.006	-0.000	0.008
	(0.005)	(0.018)	(0.036)	(0.019)
24	0.016	0.004	0.001	0.017
	(0.005)	(0.020)	(0.042)	(0.021)

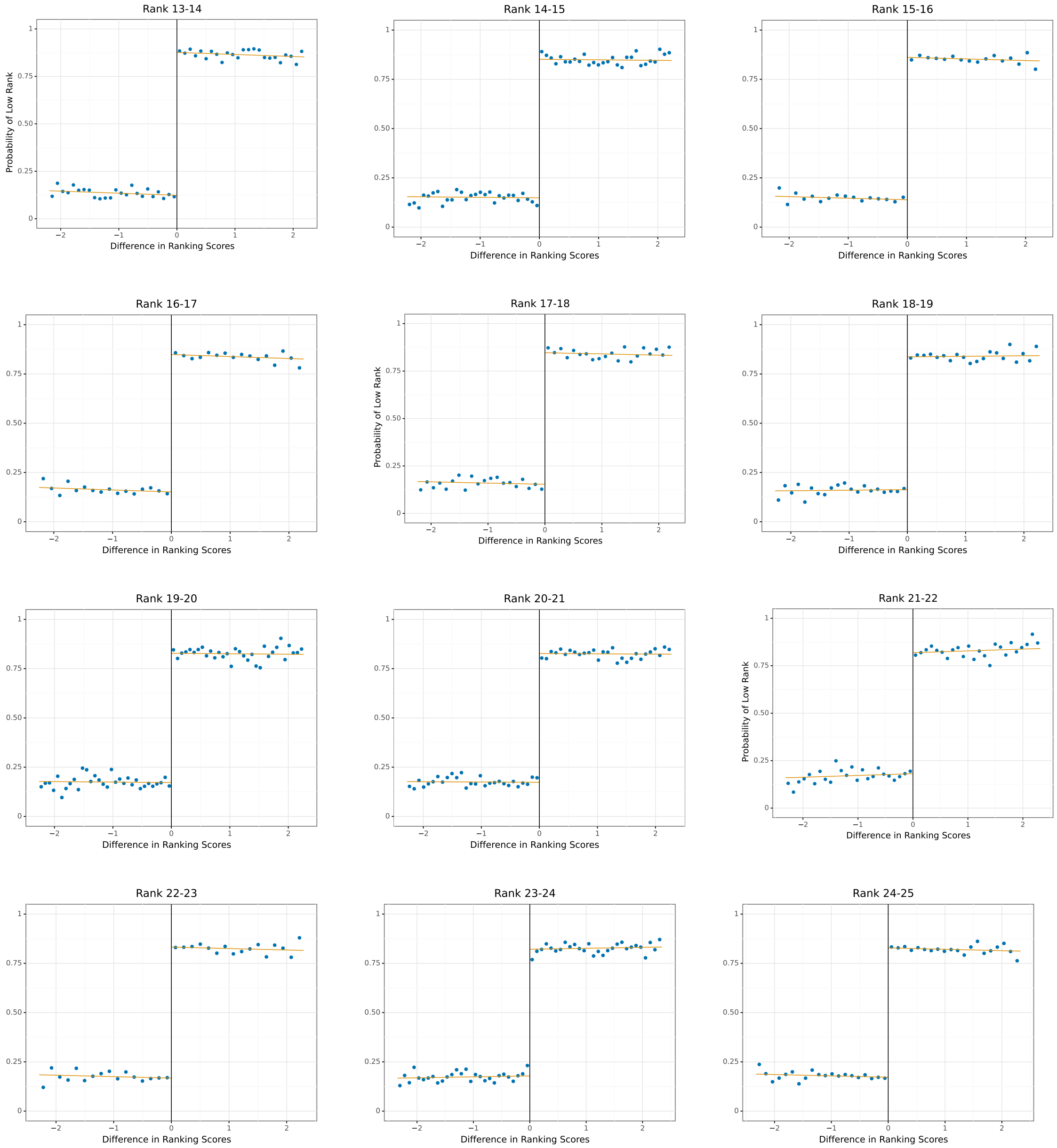
Note: Estimates of the local average treatment effect from a post moving from position $r+1$ to position r on the feed on the log-number of comments a post receives. Robust bias-corrected standard errors that allow for misspecification of the conditional expectation function and that are clustered at the period level are shown in parenthesis. Estimates exclude posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05.

Figure B.2: Regression Discontinuity Plots: First Stage



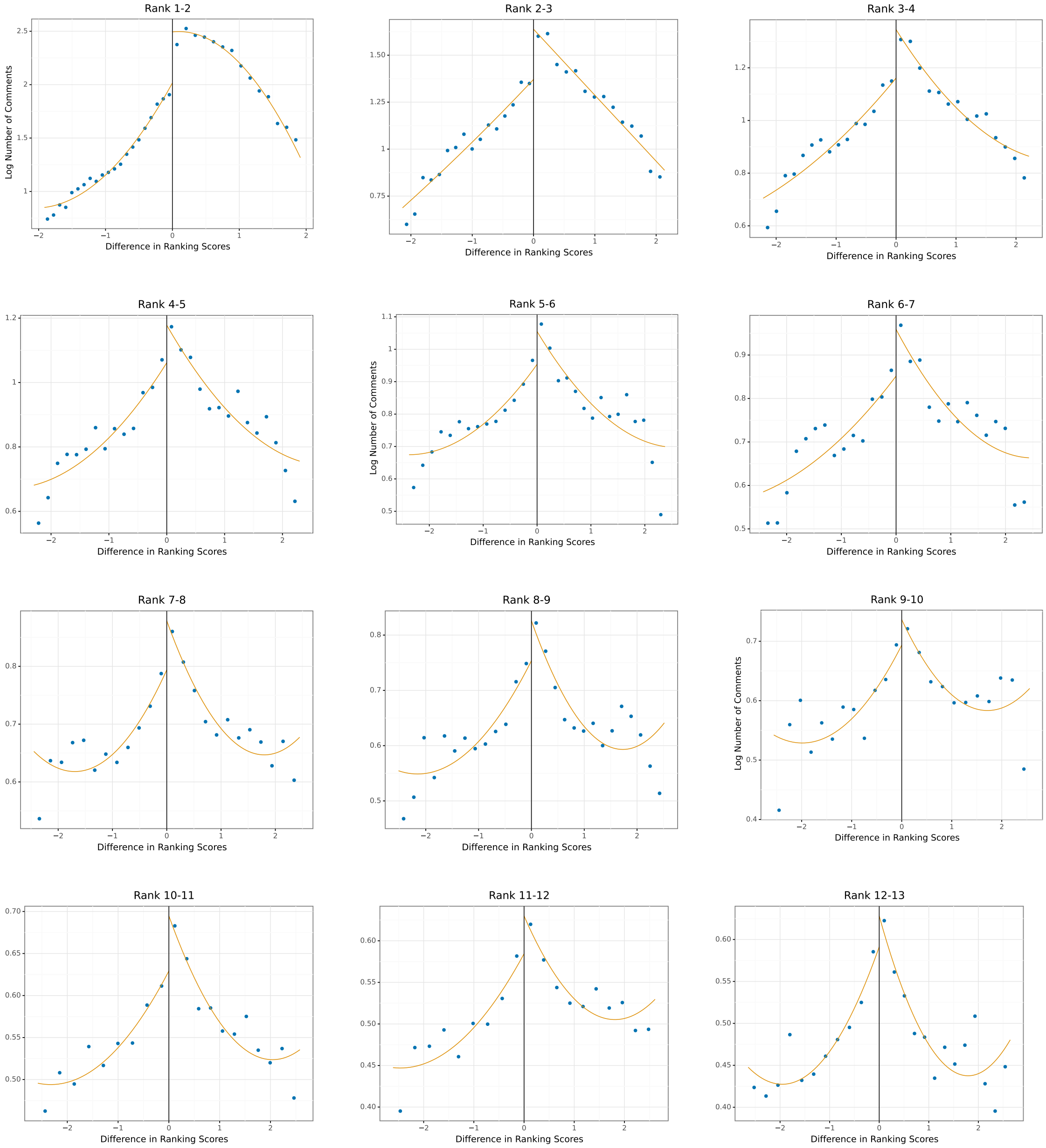
Note: Regression discontinuity first stage plots of the probability a post is ranked lower on the feed against the running variable. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. Fourth order polynomial is plotted alongside the binned mean values.

Figure B.3: Regression Discontinuity Plots: First Stage



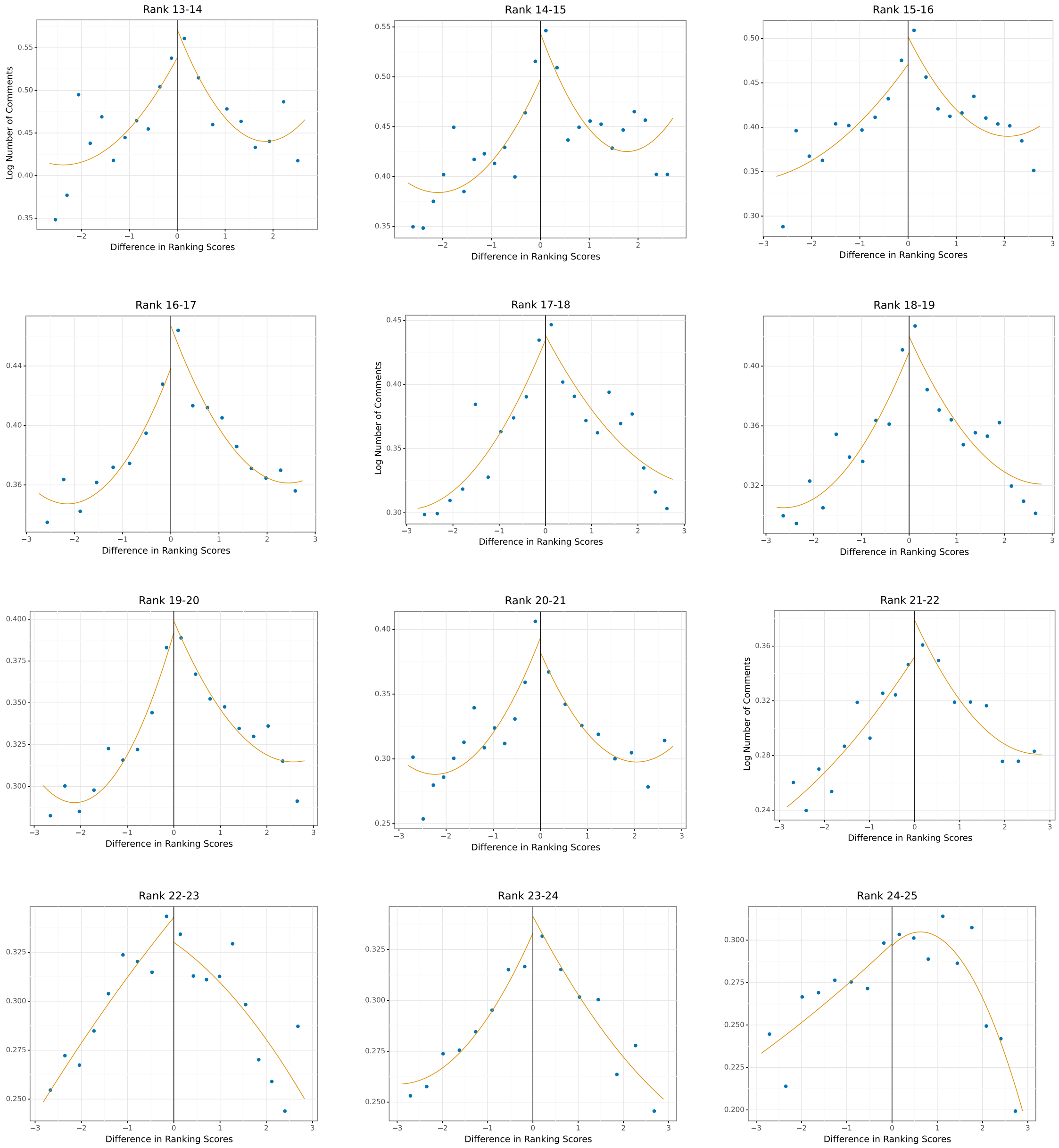
Note: Regression discontinuity first stage plots of the probability a post is ranked lower on the feed against the running variable. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. Fourth order polynomial is plotted alongside the binned mean values.

Figure B.4: Regression Discontinuity Plots: Engagement



Note: Regression discontinuity outcome plots of the log number of comments received in the 20 minutes following a snapshot against the running variable. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. Fourth order polynomial is plotted alongside the binned mean values.

Figure B.5: Regression Discontinuity Plots: Engagement



Note: Regression discontinuity outcome plots of the log number of comments received in the 20 minutes following a snapshot against the running variable. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. Fourth order polynomial is plotted alongside the binned mean values.

B.2 Robustness of Regression Discontinuity

B.2.1 Regression Discontinuity with Two-Dimensional Score

Recall the running variable in the regression discontinuity analysis is a composition of two continuous scores, the difference in vote scores and the difference in post age. Figure B.6 plots the joint distribution of these two scores along the discontinuity frontier.

B.2.2 Balance of Covariates

Here, I show evidence that pre-treatment observable post features are continuous through the discontinuity. I show the full regression discontinuity plots for the top 12 positions on the feed for post vote score (Figure B.7), post age (Figure B.8), publisher slant (Figure B.9), and publisher credibility (Figure B.10). Estimates of the local average treatment effect on each of these covariates using local linear regression are displayed in Figure B.11.

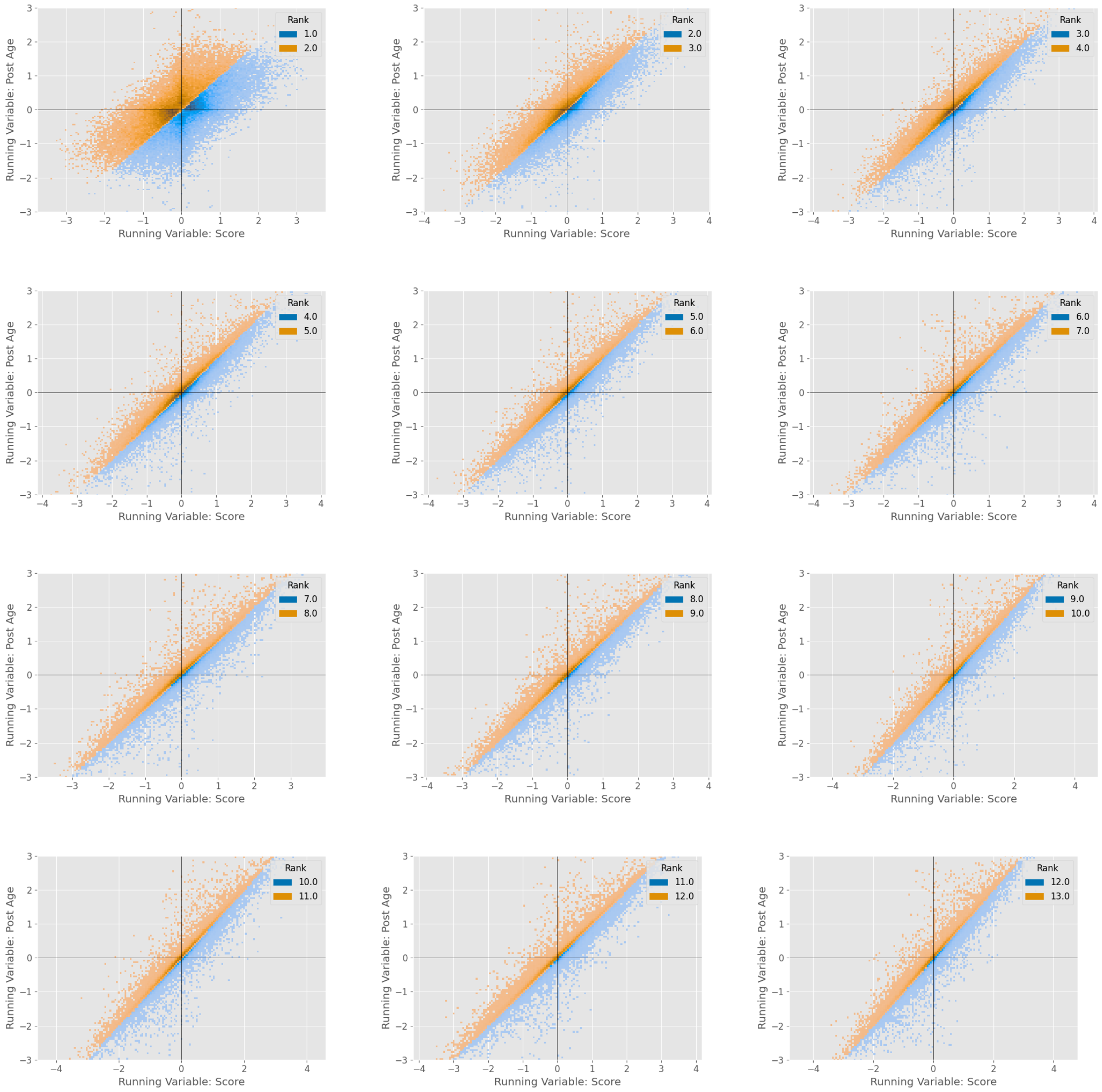
B.2.3 Robustness of Bandwidth, Donut, and Comment Window

Here, I show the position effect estimates are robust to researcher choices regarding the regression discontinuity bandwidth (Figure B.12), the donut of data excluded around the discontinuity (Figure B.13), and the window of comments included after a post snapshot (Figure B.14).

B.3 Recommender System Appendix

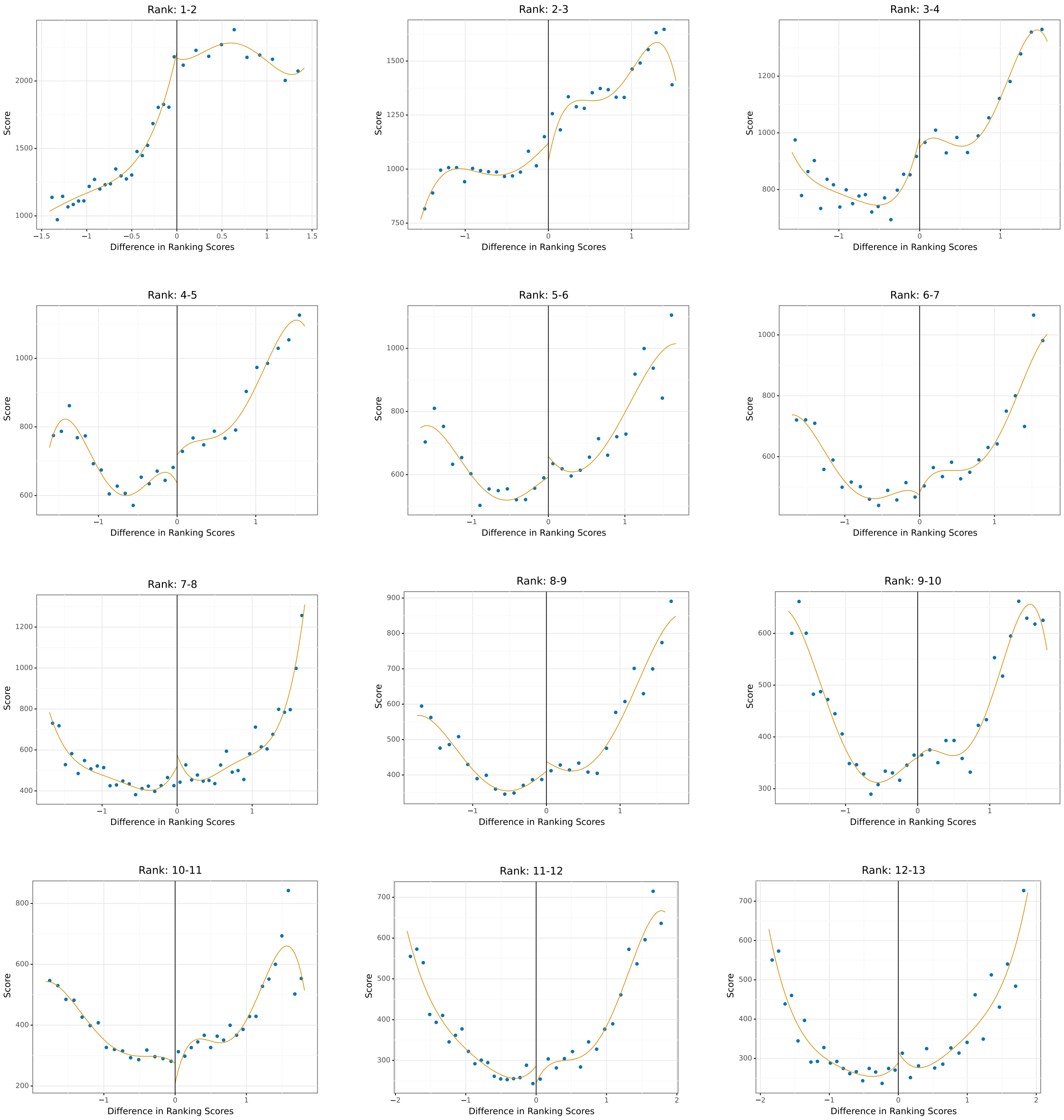
Table B.3 shows the projection of the first 3 principal components of the publisher features learned in the collaborative filtering model onto the vector of publisher ratings. These regressions demonstrate that the publisher ratings do explain some of the variation in the publisher features learned by the recommender system.

Figure B.6: Regression Discontinuity with Multiple Scores



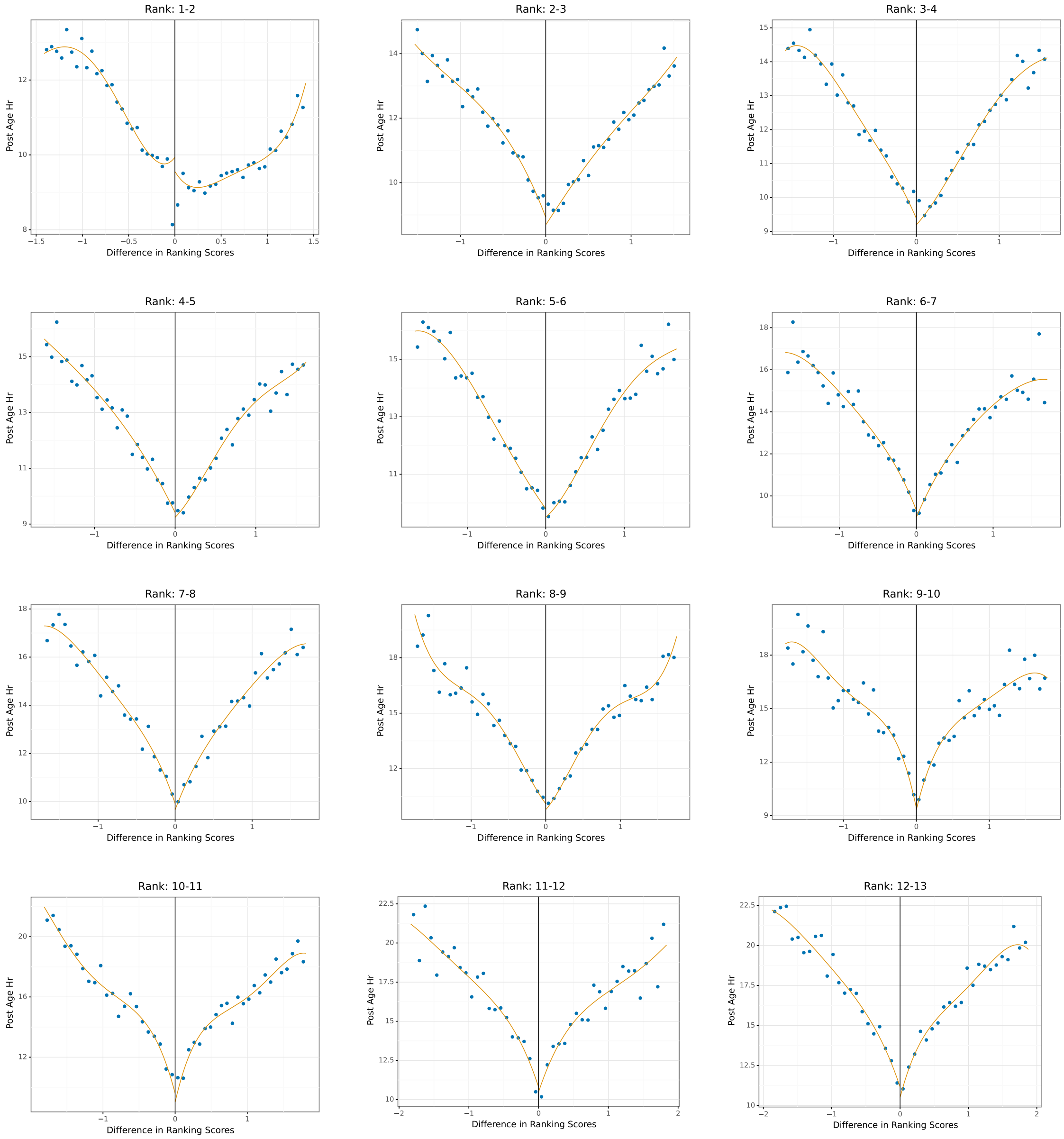
Note: This plot shows the regression discontinuity in two dimensions. The. x axis plots the difference in the normalized post vote scores and the y axis plots the difference in the normalized post ages. The discontinuity frontier corresponds to the 45 degree line. To make the charts easier to view, I only plot posts that are correctly classified by the running variable.

Figure B.7: Balance of Vote Score



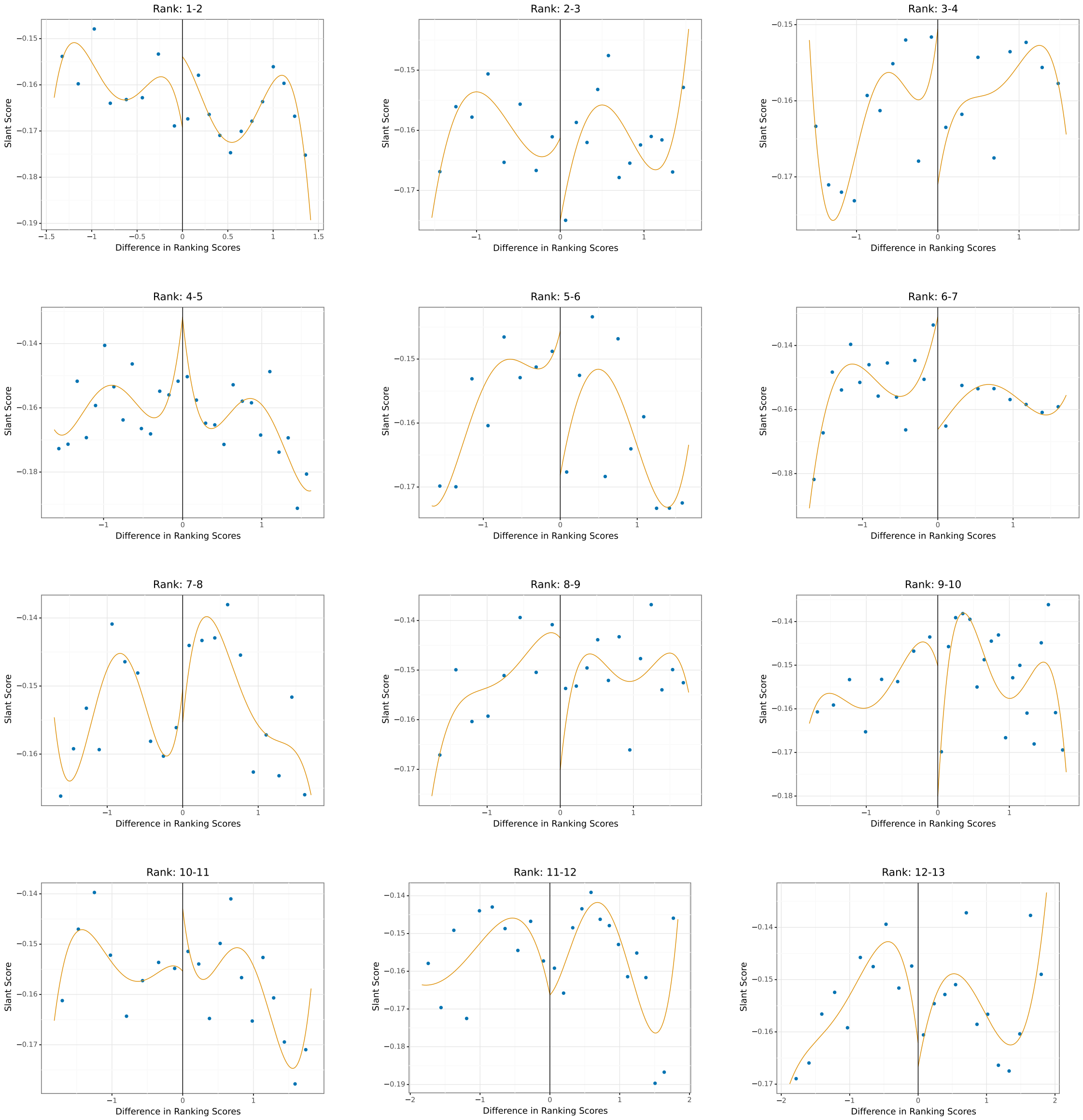
Note: This plot shows the binned means of post vote score against the running variable on the top 12 positions on the feed. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. The line represents the fourth order polynomial fit.

Figure B.8: Balance of Post Age



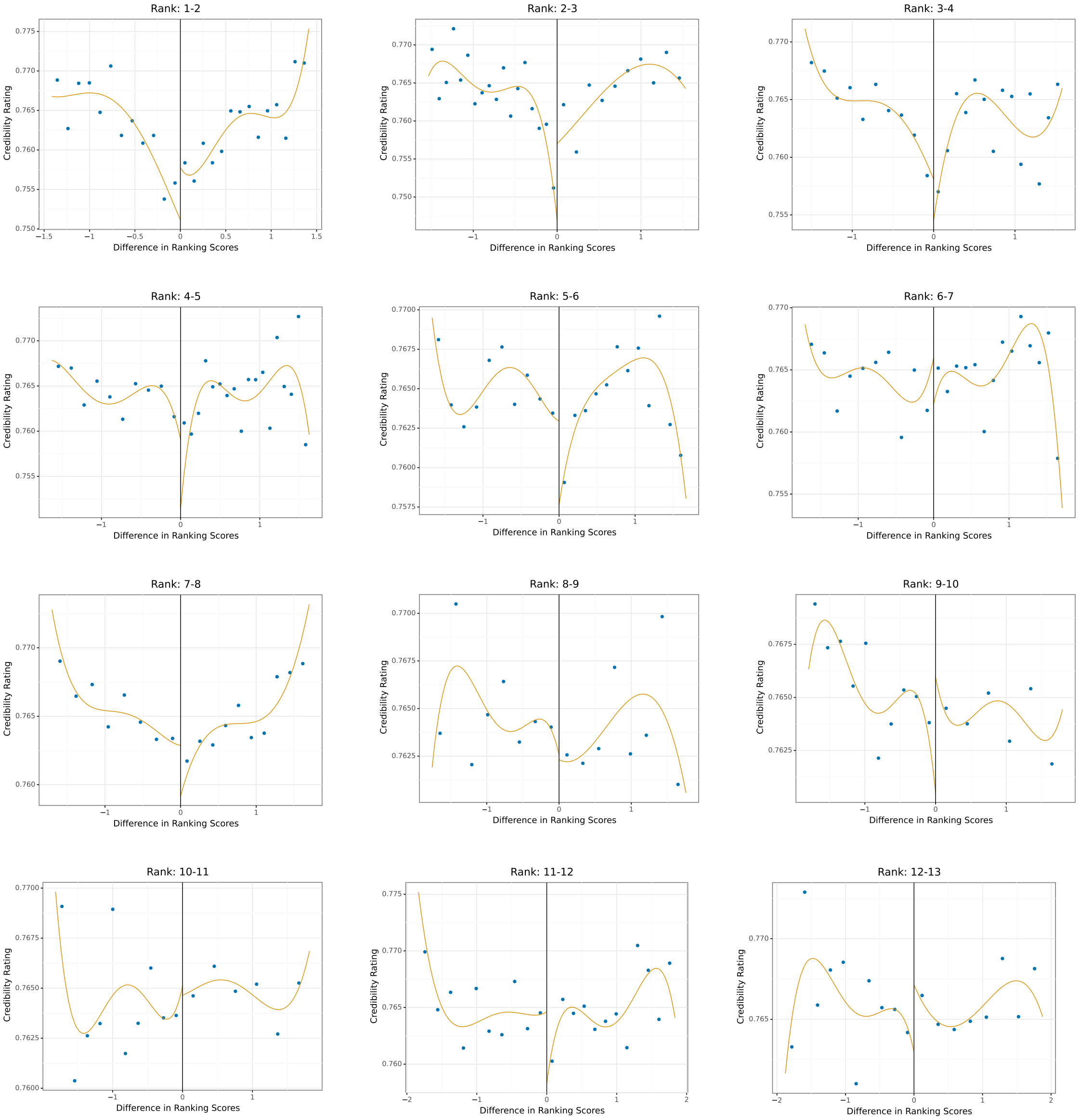
Note: This plot shows the binned means of post age against the running variable on the top 12 positions on the feed. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. The line represents the fourth order polynomial fit.

Figure B.9: Balance of Slant Score



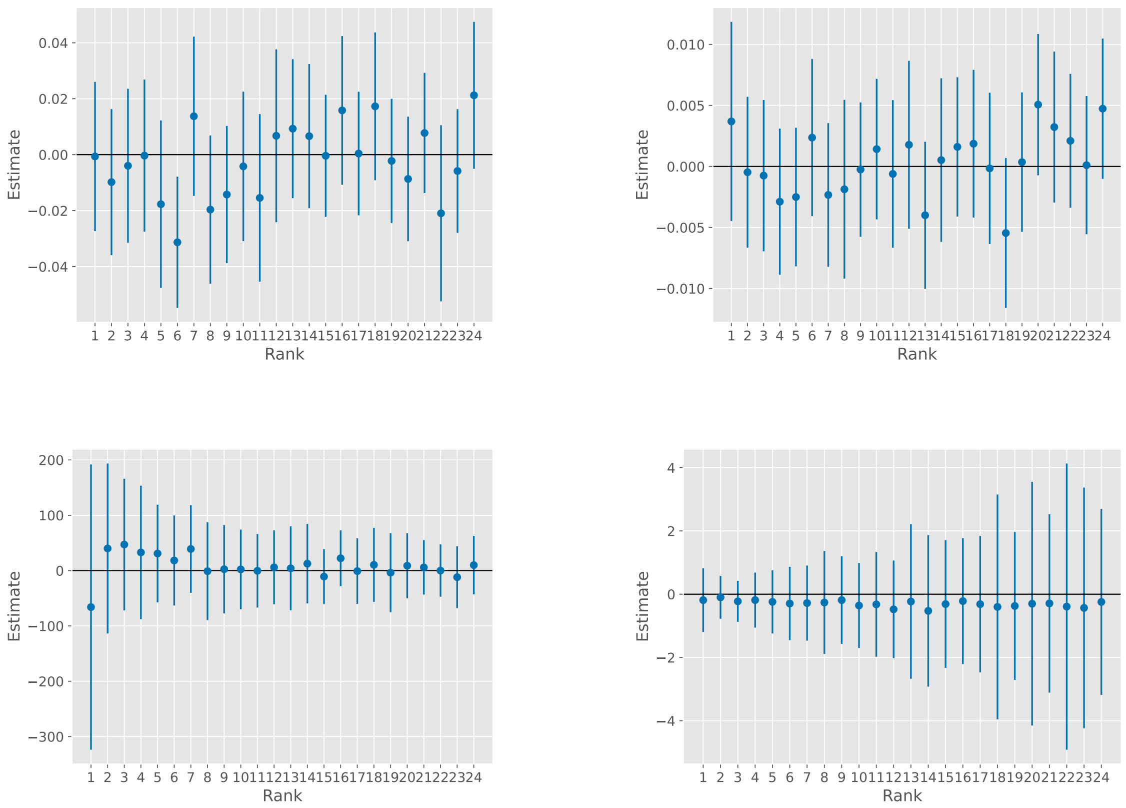
Note: This plot shows the binned means of publisher slant score against the running variable on the top 12 positions on the feed. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. The line represents the fourth order polynomial fit.

Figure B.10: Balance of Credibility Rating



Note: This plot shows the binned means of publisher credibility rating against the running variable on the top 12 positions on the feed. This figure excludes posts within the doughnut which includes posts where the absolute value of the running variable is less than 0.05. The line represents the fourth order polynomial fit.

Figure B.11: Regression Discontinuity Placebo Tests



(a) Publisher Slant

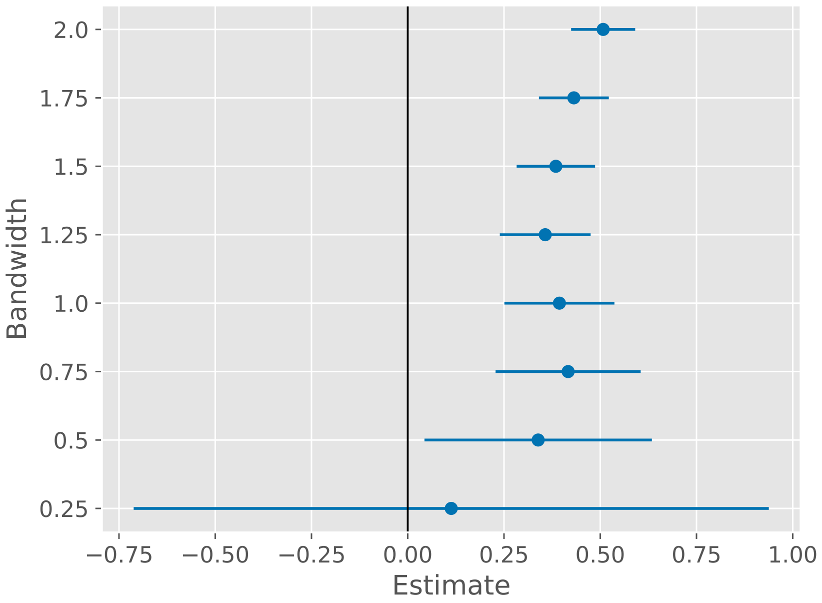
(b) Hour Posted

(c) Vote Score

(d) Post Age (hours)

Note: Placebo test for discontinuity of observable pre-treatment covariates. Each figure plots local average treatment effect estimates of moving from rank $r+1$ to rank r using a local linear regression for publisher slant score, hour posted, vote score, and post age.

Figure B.12: Robustness of Position Effect Estimates to Bandwidth



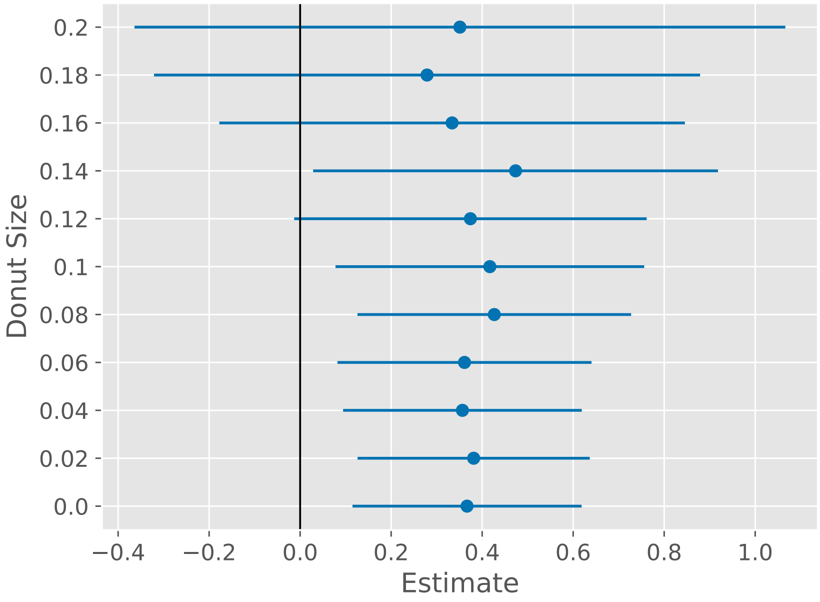
Note: This plot shows the robustness of the position effect estimate to bandwidth size. Each point represents the treatment effect estimate of being promoted to the top position on the feed relative to the second position on the log number of comments a post receives. Error bars represent 95% confidence intervals using robust bias-corrected standard errors.

Table B.3: Recommender System Publisher Factors

	(1)	(2)	(3)
Slant Score	-0.19***	0.01	-0.06**
	(0.03)	(0.03)	(0.03)
Credibility Rating	-0.00	0.00	-0.01
	(0.04)	(0.03)	(0.03)
Average Rank	0.03	0.00	-0.03*
	(0.02)	(0.01)	(0.02)
Quantity	0.11***	0.63***	0.25***
	(0.04)	(0.15)	(0.09)
Intercept	-0.07**	-0.05**	0.19***
	(0.03)	(0.02)	(0.03)
Obs	1378	1378	1378
R^2	0.05	0.39	0.08

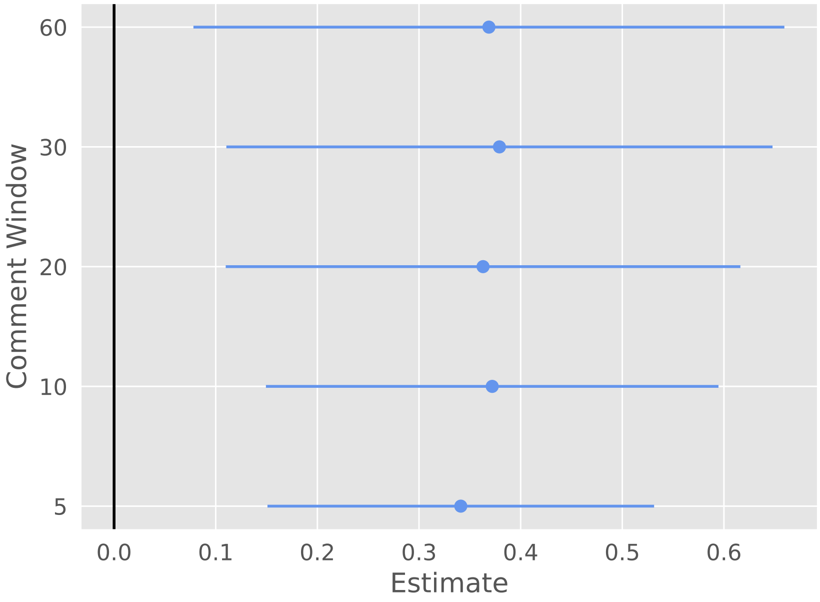
Note: This table shows estimates from a regression of the first 3 principal components of publisher features on publisher observables.

Figure B.13: Robustness of Position Effect Estimates to Donut Width



Note: This plot shows the robustness of the position effect estimate to donut size. Each point represents the treatment effect estimate of being promoted to the top position on the feed relative to the second position on the log number of comments a post receives. Error bars represent 95% confidence intervals using robust bias-corrected standard errors.

Figure B.14: Robustness of Position Effect Estimates to Comment Window

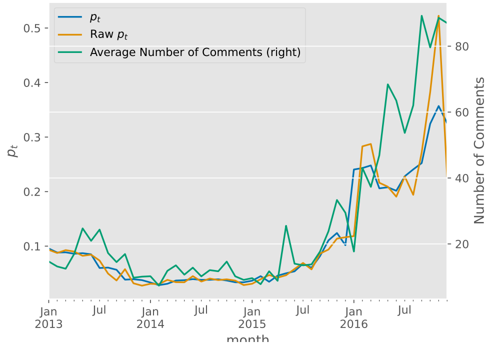


Note: This plot shows the robustness of the position effect estimate to window length. Each point represents the treatment effect estimate of being promoted to the top position on the feed relative to the second position on the log number of comments a post receives in the window following a snapshot. Error bars represent 95% confidence intervals using robust bias-corrected standard errors.

C Choice Model Appendix

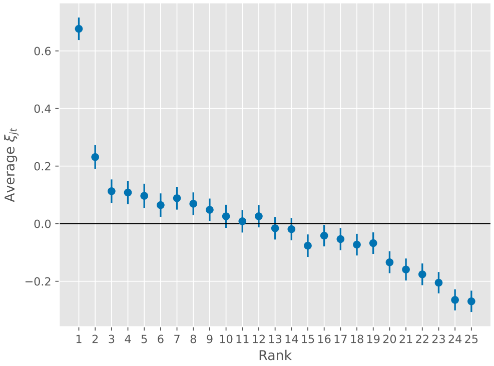
C.1 Additional Figures and Tables

Figure C.15: p_t and Average Top-Post Engagement



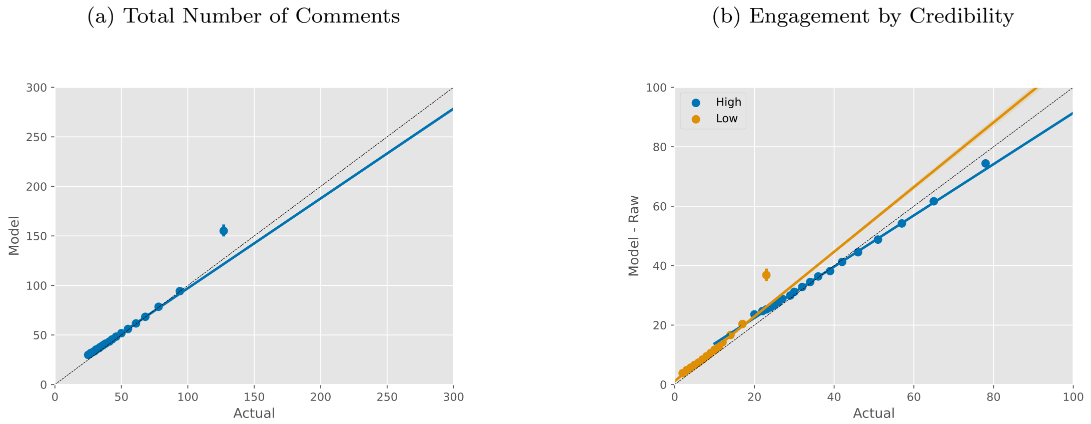
Note: This plot shows the time series of the raw and smoothed p_t estimates (left axis). The right axis shows the average number of comments the top post on the feed receives from the users in the sample.

Figure C.16: Average ξ_{jt} by Rank



Note: This plot shows the average ξ_{jt} value by post rank for the posts in the sample. Bars represent 95% confidence intervals.

Figure C.17: Summary of Model Fit

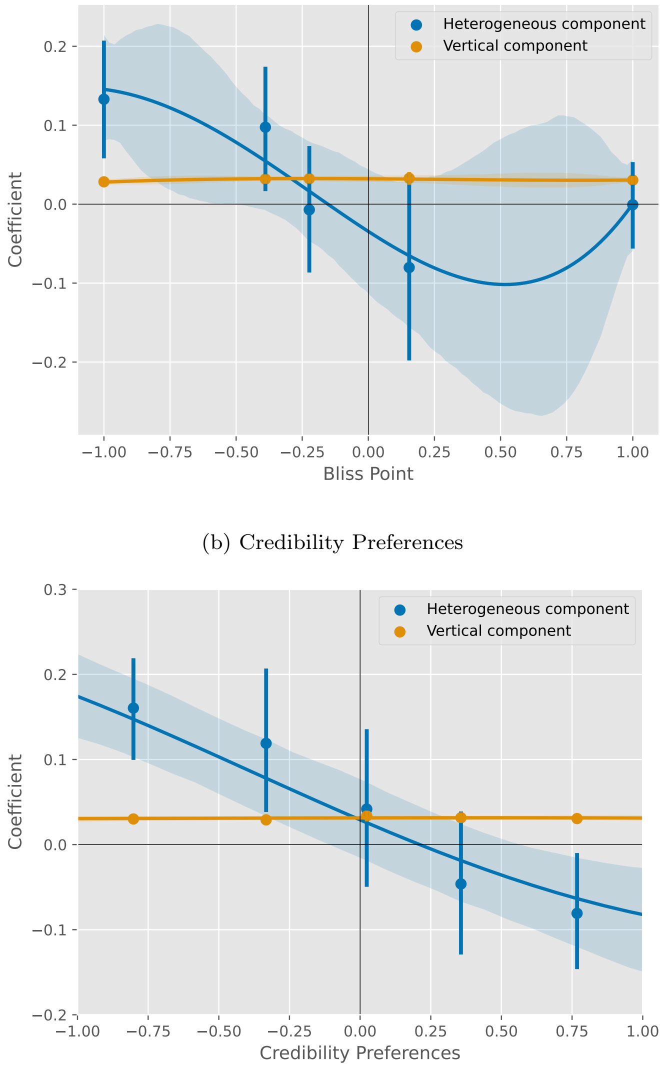


(a) Total Number of Comments

(b) Engagement by Credibility

Note: This plot shows additional summaries of the model fit. (a) The relationship between the actual number of comments a user posts against the model fitted number of comments the user submitted. (b) The same relationship, broken out by publisher credibility.

Figure C.18: Correlation of Sentiment Preferences with Comment Preferences

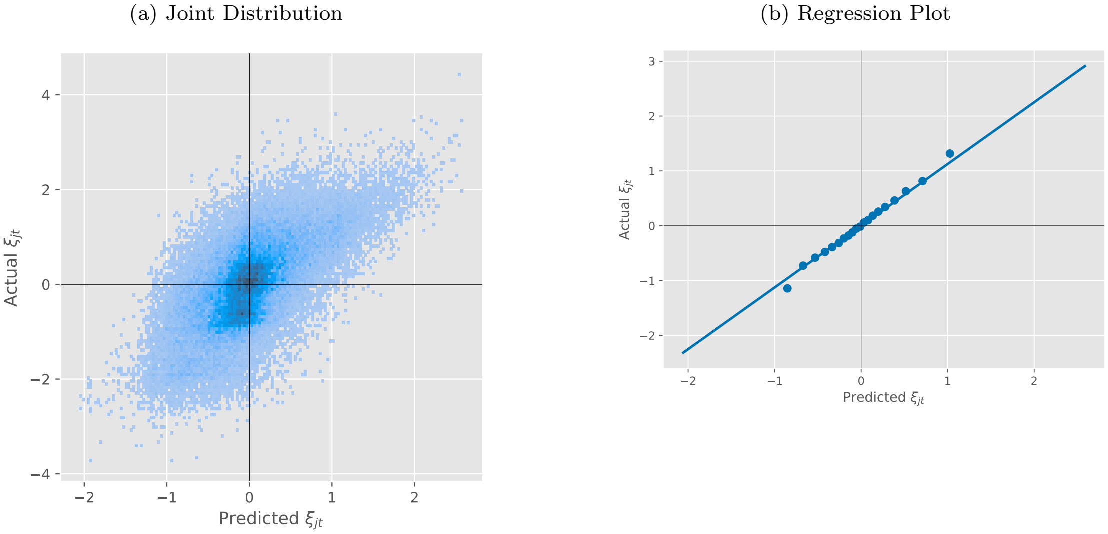


(a) Slant Bliss Point

(b) Credibility Preferences

Note: This figure plots binned mean sentiment preferences against (a) user bliss points and (b) credibility preferences. The heterogeneous component captures how the likelihood of a user to submit a negative comment changes in response to changes in the user-specific component of post comment utility. The vertical component captures how the likelihood of a user to submit a negative comment changes in response to a change in the latent commentability term (ξ_{jt}). Positive values mean the user is more likely to submit a negative comment on articles they are likely to comment on. Regression line is a fourth-order polynomial fit. Confidence bands represent 95% confidence intervals.

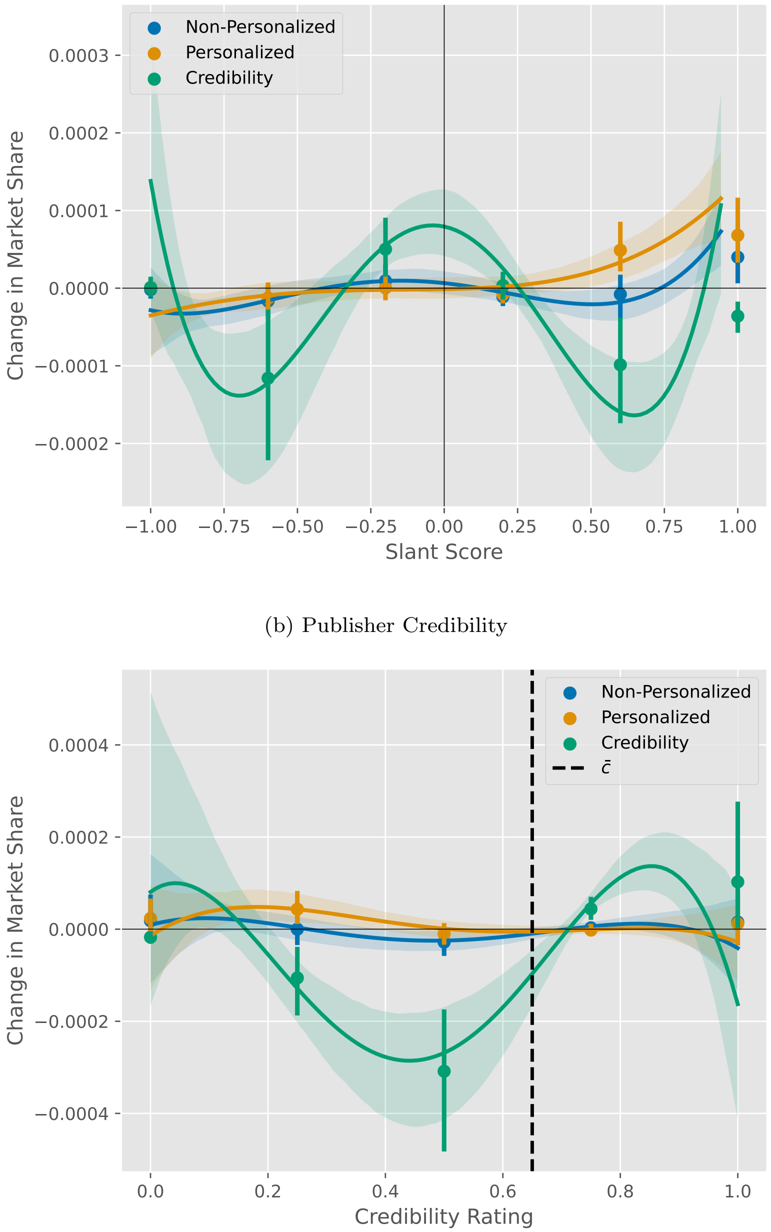
Figure C.19: Summary of ξ_{jt} Model


(a) Joint Distribution

(b) Regression Plot

Note: This plot shows a summary of the random forest model used in the counterfactuals to estimate ξ_{jt} in each period. (a) shows the joint distribution between ξ_{jt} and $\hat{\xi}_{jt}$ and (b) shows binned means of this relationship along with a linear fit.

Figure C.20: Change in Publisher Market Shares



(a) Publisher Slant

(b) Publisher Credibility

Note: Figure C.20a plots the binned mean change in publisher market share by publisher slant and Figure C.20b plots the binned mean change in publisher market share by publisher credibility rating. In both figures, the regression lines are fourth-order polynomial fits. Confidence bands represent 95% confidence intervals.

C.2 Empirical Bayes Shrinkage

To shrink individual preference estimates towards the grand mean and adjust for the over-dispersion due to sampling error I use the following empirical Bayes procedure. I assume that the true individual preference parameters are drawn independently and identically distributed from a multivariate normal distribution

$$\beta_i \sim N\left(\mu, \Sigma\right)$$

and we observe noisy estimates of these parameters $\hat{\beta}_i = \beta_i + \nu_i$ where $\nu_i \sim N\left(0, \Sigma_i\right)$ is independent sampling error and Σ_i are estimated covariance matrices of preferences for each user. I form estimates of the grand-mean and covariance matrix using empirical analogs of the following expectations.[22]

$$\mu = E\left[\hat{\beta}_i\right]$$

$$\Sigma = E\left[\left(\hat{\beta}_i - \mu\right)\left(\hat{\beta}_i - \mu\right)'\right] - E\left[\Sigma_i\right]$$

and then form estimates of the posterior mean for each β_i as

$$E\left[\beta_i | \hat{\beta}_i, \Sigma_i, \mu, \Sigma\right] = \left(\Sigma^{-1} + \Sigma_i^{-1}\right)^{-1}\left(\Sigma^{-1}\mu + \Sigma_r^{-1}\hat{\beta}_i\right).$$

This shrinks each estimated preference parameter towards the grand mean and corrects for the over-dispersion created by sampling error.

C.3 Estimating the Share of Users Accessing the Platform

Little's law shows that in a stationary system, the average number of users on the platform can be expressed as

$$L_t = \lambda_t W \tag{14}$$

where L_t is the average number of users on the platform at any point during period t, λ_t is the arrival rate of customers during period t, and W is the average session length [Little, 1961]. I assume $W = 10.82$ given that the average session length on Reddit in 2016 lasted 10 minutes and 49 seconds.[23] I assume that the number of users $A_t^0 = L_t$: the number of users online at the start of each period is equal to the average over the period. I can re-arrange equation 14 to show that $A_t = \frac{l}{W} A_t^0$ which says the total number of users to visit the platform during period t (A_t) equals the length of the period in minutes (l) divided by the session length (W) multiplied by the number of users online at any given time. To calibrate the number of active community members in a subreddit, I use two snapshots of the politics community's usage statistics from 2015 and 2016

[22] When estimating the grand mean, I use inverse variance weights to improve precision of the estimated mean.

[23] `https://web.archive.org/web/20161203082123/https://www.similarweb.com/website/reddit.com/`

to calculate the average number of unique users per day.[24] When combined with the number of subscribers a community has, I can estimate the share of subscribers that are active in a given day which averages 0.071 over the months covered in the two snapshots. I then calculate $N_t = 0.071 \times S_t$ where S_t is the number of subscribers the community has at period t. Robustness to the scaling factor is shown in Appendix Section C.4. Finally, I smooth estimates of p_t by taking the fitted values of the following regression model

$$\frac{A_t}{N_t} = \gamma_0 + \gamma_{quarter} + \gamma_{day} + \eta_t \tag{15}$$

where $\gamma_{quarter}$ and γ_{day} are quarter and day of week fixed effects, respectively.

C.4 Choice Model and Counterfactual Robustness

C.4.1 Robustness to Scaling $p(\cdot)$

First, I show that the counterfactual results are robust to scaling the exposure probability $p(\cdot)$ in the choice model. This shows the results are robust to the decision to scale the number of active users in Section C.3 and to the assumption that all users are exposed to the first post in the feed ($p_1 = 1$) as both simply multiply either p_t or p_r by a constant, so showing $p(\cdot)$ is robust to being multiplied by a constant demonstrates robustness to both.

[24] `https://web.archive.org/web/20160905095430/https://www.reddit.com/r/politics/about/traffic`
`https://web.archive.org/web/20150513102644/http://www.reddit.com/r/politics/about/traffic/`

Table C.4: Counterfactual Engagement Summaries Robustness: $p'(\cdot) = 0.5p(\cdot)$

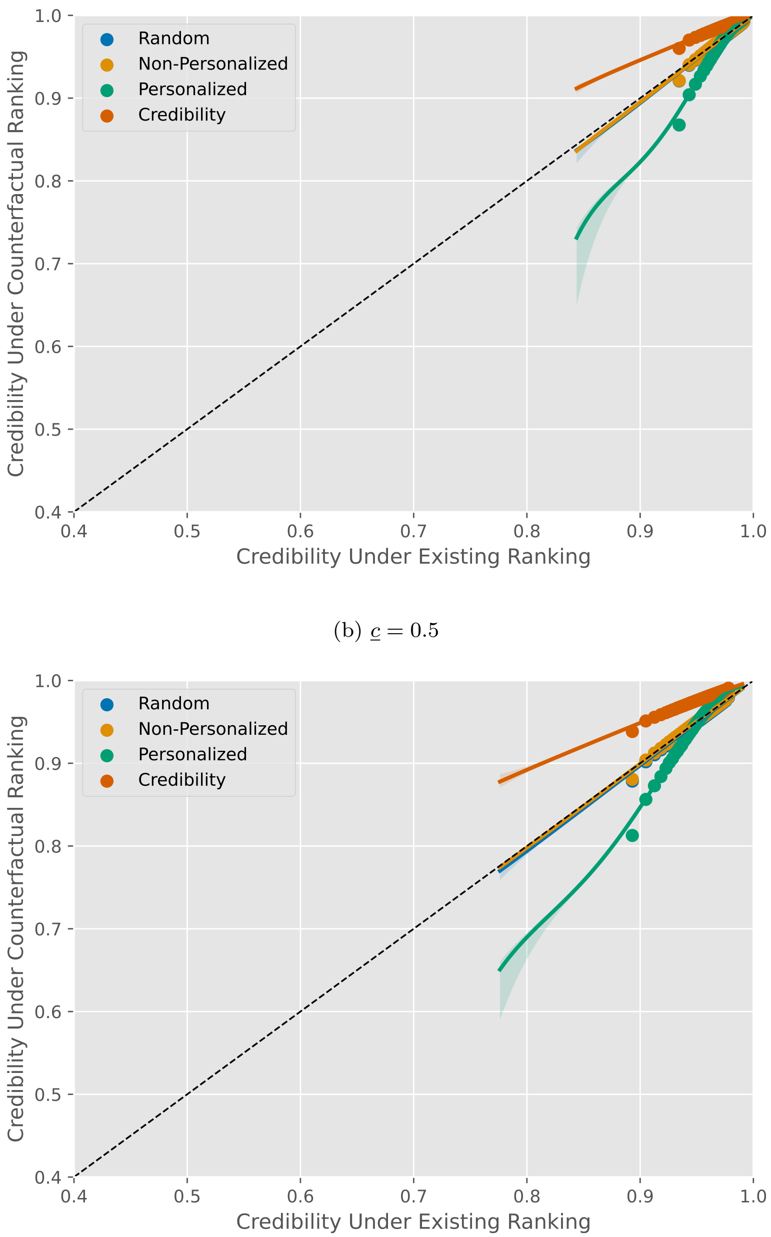
	Engagement	Diversity	Max Partition Share	Credibility	Negative Engagement Share
Intercept	53.537	1.519	0.290	0.791	0.512
	(0.376)	(0.000)	(0.000)	(0.000)	(0.002)
Random	-6.144	0.005	-0.001	-0.000	-0.001
	(0.037)	(0.000)	(0.000)	(0.000)	(0.000)
Non-personalized	11.211	0.003	-0.005	0.010	0.002
	(0.057)	(0.000)	(0.000)	(0.000)	(0.000)
Personalized	12.270	-0.017	0.021	0.000	0.002
	(0.066)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	33340	33340	33340	33340	33340
R-Squared	0.043	0.048	0.074	0.006	0.000

Note: This table reports estimates of a panel regression of each counterfactual outcome on counterfactual algorithm dummy variables in the robustness exercise where $p(\cdot)$ is multiplied by a factor of 0.5. The intercept is the average quantity under the existing algorithm. Standard errors are clustered at the user level.

C.4.2 Robustness to Choice of $\underline{c}$

I replicate the quality analysis for various choices of $\underline{c}$ and find the results are qualitatively similar (Figure C.21). For values of $\underline{c}$ as low as 0.4, I find the personalized engagement maximizing exacerbates differences in users along the credibility dimension. As the threshold for credibility is lowered, by definition the share of high quality engagement rises as the threshold does not impact the counterfactuals directly, only how the counterfactuals are evaluated.

Figure C.21: High-Credibility Share by Baseline Credibility: Robustness



(a) $\underline{c} = 0.4$

(b) $\underline{c} = 0.5$

Note: This figure plots binned mean credibility shares under the counterfactual algorithm against credibility shares under the existing algorithm for various thresholds of high-quality publishers. Regression line is a fourth-order polynomial fit. Confidence bands represent 95% confidence intervals.