News Feeds and User Engagement: Evidence from the Reddit News Tab

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We study how the introduction of a new non-personalized news feed impacts user engagement quantity, quality, and diversity on Reddit. In June 2018, Reddit introduced the News tab on iOS devices that surfaces popular content from a curated list of news-related communities. We leverage this natural experiment to identify the causal effects of the News tab on iOS user engagement in a difference-in-differences design. We find that the News tab increases the share of iOS devices that engage with news-related content and the new engagement is not meaningfully different in quality from existing engagement. Additionally, we find that the diversity of engagement within news categories and within articles from publishers across the political spectrum increases as a result of the News tab. These results suggest that non-personalized feeds can be an important tool to mitigate algorithmic filter bubbles.

Key words: Social media; Filter bubbles; News feeds; User Engagement

1. Introduction

Social media platforms play an important role in everyday life, with the average person with access to the internet spending over two hours daily on social media (Kemp 2020). The prevalence of social media in modern life has important implications for individual well-being (Allcott et al. 2020), the quality of news people consume (Vosoughi et al. 2018), and political polarization (Levy 2021). Many of the largest social media platforms are organized around news feeds, which aggregate content from across the platform (e.g. Facebook News Feed and Twitter timeline). A growing body of research has demonstrated the importance of news feed algorithms on individual well-being (Kramer et al. 2014), platform engagement (Dujeancourt et al. 2021), and exposure to counter-attitudinal news (Bakshy et al. 2015, Levy 2021, Huszár et al. 2021).

Here we study the effects of Reddit, a large social media platform, introducing a supplementary non-personalized news feed on engagement quantity, quality, and diversity.[1] We leverage a natural experiment on the Reddit platform, where a News tab that surfaces popular content from a curated list of news-related communities was introduced on iOS devices but not desktop or Android devices.[2] At the time, Reddit statements indicated the iOS only roll out was to test and improve the feed and the platform had plans to introduce this feature across all devices. Therefore, we view this as an exogenous change to the app and argue that, absent the introduction of the News tab, Reddit engagement trends would have been similar across Android and iOS users. This allows us to identify the causal effect of the News tab using a difference-in-differences strategy.

We find that the introduction of the news feed induces a statistically significant increase in the probability of posting any content on a news-related community. This increase is concentrated in the Politics (23.8%), Technology (13.8%), and Business (84.0%) related communities that were featured in the News tab. In addition, we find the comments induced by the News tab are similar in quality to the existing comments, as measured through voting on the platform, comment length, and comment sentiment. Finally, the non-personalized feed also increases individual engagement diversity as implemented through the Shannon Entropy (Shannon 1948, Holtz et al. 2020), Herfindahl–Hirschman Index (Rhoades 1993,

[1] Our analysis focuses on user commenting behavior and throughout we will use engagement and posting a comment interchangeably. We discuss this choice further in the data and discussion sections.

[2] Throughout we use the term community to refer to a subreddit.

Claussen et al. 2019), and breadth of engagement (Datta et al. 2018). This is true both for the diversity of engagement across the communities included in the News tab in addition to the diversity of engagement across articles from publishers of different political slant. The effects on engagement quantity and diversity are largest among existing active users of the platform, suggesting this feed worked primarily by encouraging diverse engagement from existing users rather than inducing new or non-posting users to engage with news.

These results have important managerial and policy implications. In particular, we highlight the effects of a supplementary news feed algorithm on engagement quantity, quality, and diversity. The increase in engagement with featured communities is beneficial for platforms that rely on advertising revenue and the creation of user-generated content by users. Moreover, our results demonstrate in this setting there was not a material decline in contribution quality due to the influx of new users, which could make the platform less valuable to existing members by increasing the costs of finding high quality discussion and information (Gu et al. 2007, Gorbatai 2014, Kiene et al. 2016). The increase in engagement diversity caused by the News tab has positive implications for user retention (Oestreicher-Singer and Zalmanson 2013, Anderson et al. 2020). That these effects are concentrated among existing users suggests that such a feed is more effective at engaging and retaining current users than encouraging new users to contribute. From a policy perspective, the increase in the diversity of engagement across publishers from various political viewpoints suggests that non-personalized feeds can be an important tool to mitigate algorithmic filter bubbles (Pariser 2011).

2. Related literature

In this paper we contribute to several streams of the existing literature. First, we add to the literature studying the impacts of social media feed algorithms on users and society. This includes work studying the impact of social media feeds on individual well-being (Kramer et al. 2014, Allcott et al. 2020), media consumption (Bakshy et al. 2015, Allcott et al. 2020, Levy 2021), exposure to content from politicians (Huszár et al. 2021), and user engagement (Dujeancourt et al. 2021). Kramer et al. (2014) find that changes to the Facebook News Feed that promote (or suppress) posts containing positive expressions cause users to post more (less) positive posts and less (more) negative posts, highlighting the importance of the News Feed algorithm in determining the content that users interact with and downstream effects on user behavior. Similarly, Bakshy et al. (2015), Allcott et al. (2020), and Levy (2021) find that the news feed impacts the news people read, and in particular, exposure to counter-attitudinal sources. In this study we contribute to this literature by studying the impact of a supplementary news feed on user engagement on a large social media platform. In particular, we investigate how the feed impacts the diversity of news users engage with, and find that the supplementary non-personalized feed can help mitigate algorithmic filter bubbles.

Second, we contribute to the growing literature studying the impacts of algorithmic recommendations on consumer behavior. This has been studied in the context of product sales (Oestreicher-Singer and Sundararajan 2012, Hosanagar et al. 2014, Lee and Hosanagar 2019) as well as content consumption (Bakshy et al. 2015, Claussen et al. 2019, Holtz et al. 2020, Dujeancourt et al. 2021, Bar-Gill and Gandal 2017). The existing work typically finds that personalized algorithms increase content consumption relative to manually curated recommendations (Claussen et al. 2019, Holtz et al. 2020) and chronologically ordered news feeds (Dujeancourt et al. 2021). In addition, Bakshy et al. (2015), Claussen et al. (2019) and Holtz et al. (2020) find (to varying extents) that personalized recommendations decrease individual consumption diversity, supporting the notion of algorithmic recommendations leading to filter bubbles. We contribute to this body of work by studying the causal effects of a new supplementary non-personalized news feed on engagement and engagement diversity. In contrast to the work studying personalized feeds (Bakshy et al. 2015, Claussen et al. 2019, Holtz et al. 2020), we find the introduction of a supplementary non-personalized news feed increases individual engagement diversity. A distinguishing feature of this study, however, is that we do not find evidence of an engagement-diversity trade-off that has often been seen in the literature (Holtz et al. 2020). That is, we do not find that the increase in engagement diversity comes at the expense of total engagement, likely due to the fact that the feed we studied was introduced as a supplementary feed and not in place of the primary news feed.

Finally, given the focus in this study on content production we also contribute to the large literature studying incentives and motivations for user generated content. Past research has investigated numerous interventions to induce additional user generated content. These interventions include financial incentives with mixed results (Cabral and Li 2015, Khern-am nuai et al. 2018, Burtch et al. 2018), successful social norm interventions (Chen et al. 2010, Burtch et al. 2018), and status or rewards (Goes et al. 2016, Restivo and Van De Rijt

2012, Gallus 2017, Burtch et al. 2021). Of particular relevance to this work are the trade-offs faced in stimulating additional user generated content. A concern managers may have when implementing policies to stimulate user generated content is understanding how the new content will impact the community. For example, Khern-am nuai et al. (2018) find that financial incentives can increase the quantity of online reviews, though these incentives result in the marginal reviews being of lower quality. Gu et al. (2007) emphasize this trade-off explicitly and study the competing positive network externalities, stemming from additional engagement providing more information, and negative externalities, if additional low-quality engagement distracts members of the community and increases costs of finding relevant information. Turning to Reddit, the focus of this study, Kiene et al. (2016) study a large influx of users to the Reddit NoSleep community and find through interviews that the community was not harmed by the influx of users. This is contrary to previous theoretical and empirical research that study Usenet's "Eternal September" (Jones et al. 2004). We contribute to this literature by studying empirically if a supplementary news feed induces additional user generated contributions and how the contributions induced by the new feed differ from the existing posts.

3. Setting

Reddit is a popular social media platform founded in 2005 with over 52 million daily active users as of January 2020.[3] The platform consists of over 100,000 active communities called subreddits, which host user-generated content focused on a particular topic. Within a community, users can post new submissions or comment on others' submissions. By default, content is presented to users using a proprietary algorithm that favors upvotes and fresher content.[4]

Voting on content is an important part of Reddit both practically, as it is a key driver of content promotion, and as a method of rewarding content that contribute to the community and demoting those that do not.[5] While norms vary within communities, Reddit guidelines are explicit that voting should reflect contributions to the community and conversation.[6] In

[3] `https://www.redditinc.com/press`

[4] The exact algorithm was publicly disclosed until 2016. See Moehring (2024) for details of the ranking algorithm and an analysis of how the algorithm impacts engagement.

[5] Upvoting (downvoting) a user's post or comment impacts their Karma score, which is a publicly available number summarizing "how much good the user has done for the Reddit community" (`https://www.reddit.com/wiki/faq`).

[6] "Vote. If you think something contributes to conversation, upvote it. If you think it does not contribute to the subreddit it is posted in or is off-topic in a particular community, downvote it." (`https://www.reddithelp.com/hc/en-us/articles/205926439`)

particular, downvoting only because you disagree with the content is explicitly discouraged and downvoting should be reserved for content that is not contributing to the community's conversation. Therefore, in this study we will use voting data to infer post quality as judged by members of the community in addition to more objective text-based measures.

Reddit is accessible to users through web browsers or mobile apps. In April 2016 Reddit launched their official mobile apps for Android and iOS devices.[7] Users of the official mobile app are able to access three primary news feeds through a navigation bar at the top of the screen: "Popular", "Home", and "News", though the News section is only available to users with iOS devices. The Popular tab aggregates popular content from across the site and the Home tab aggregates content from communities in which the user is a member. The News tab is the focus of this study and is discussed in detail in Section 3.1.

3.1. Natural Experiment

In June 2018, Reddit introduced an update to its mobile app on Apple (iOS) devices that introduced the News tab, which provided a feed of content from communities that focus on discussion and sharing of news related content. The tab is displayed prominently in the mobile app alongside the Home tab that shows submissions from communities a user is a member of and the Popular tab that shows popular content from across the platform (Figure 1). Within the News tab, users first view a feed containing posts from all news categories. Users may then select individual topics to view more focused feeds that display posts related to the selected topic. The communities that are displayed in the News tab are chosen to be those that most often engage with news, who are actively moderated and in compliance with Reddit policies on acceptable content and guidelines for healthy communities, and who require the title of posts linking to news articles to be an accurate reflection of the article title. These guidelines result in most posts in the News tab following a common structure, where the post title is an article headline and the body links to the full article (Figure 1).

In Reddit's public comments at the time, they announced that the News tab was originally being released on iOS, but would eventually be available on most devices.[8] Our empirical strategy, which will be discussed in greater detail in Section 4.3, relies on the assumption

[7] Before the official Reddit apps were supported, there were a number of third party apps that allowed users to browse the site and many unofficial apps are still available today, though the official Reddit app is the dominant app in the market.

[8] `https://www.reddit.com/r/announcements/comments/8sth30/extra_extra_were_launching_a_news_tab_as_a_beta`

Figure 1 Screenshot of Reddit News tab

that, absent the introduction of the News tab, engagement trends of iOS users in our sample would have followed engagement trends of Android users in our sample.[9] We provide evidence consistent with such an assumption in Section 4.4, though the assumption cannot be explicitly tested empirically.

4. Data

The data for this study are based on a dataset of public Reddit submissions and comments described in Baumgartner et al. (2020).[10] We focus on posts between June 2017 and December

[9] Our preferred results require a slightly weaker assumption that common trends hold conditional on observed pre-treatment engagement. This is because we use Coarsened Exact Matching weights in the analysis (Iacus et al. 2012), described in Appendix A.

[10] Gaffney and Matias (2018) find evidence of missing data in this dataset. In particular, they find that less than 0.04% of comments and 0.65% of submissions are missing from the dataset in the early years. We believe missing data

2018 which contain a total of 349 million submissions and 3.0 billion comments during this period, but restrict our sample to the subset of users for whom we can infer their mobile device.[11] The final sample has 14.1 million total comments across all communities during the period. We focus on comments rather than submissions, as comments make up the majority of posts and this is particularly evident in communities promoted on the News tab.[12] Descriptive statistics for our sample are displayed in Table 1.

	Any Post	Number of Posts		Any Negative Score		Any Positive Score	
	Mean	Mean	SD	Mean	$P(any\|posting)$	Mean	$P(any\|posting)$
All Posts	0.625	541.1	1611.0	0.464	0.742	0.624	0.998
All News	0.374	40.9	300.3	0.166	0.444	0.369	0.985
US/World	0.213	5.6	48.7	0.074	0.349	0.206	0.969
Politics	0.106	6.3	114.9	0.036	0.338	0.102	0.960
Technology	0.142	1.4	17.1	0.031	0.217	0.137	0.965
Science	0.117	1.1	17.2	0.019	0.160	0.113	0.965
Sports	0.131	16.6	230.1	0.045	0.346	0.127	0.973
Gaming	0.178	6.4	72.6	0.051	0.287	0.173	0.976
Entertainment	0.172	3.2	34.4	0.042	0.242	0.167	0.969
Business	0.014	0.1	3.3	0.003	0.181	0.014	0.951

Table 1 Sample summary statistics

Summary statistics for our sample. We aggregate across periods for a single user, and then report summary statistics of these user aggregates.

on this scale is unlikely to be driving our results for two reasons. First, as discussed in Baumgartner et al. (2020), the data collection process has improved as a result of the flaws highlighted in Gaffney and Matias (2018) which analyze data before the period studied here. Second, Gaffney and Matias (2018) find that heavy users are more likely to be impacted than light users. Our primary outcomes are indicators if a user posted *any* posts in a month. Therefore, for the outcome to be changed we would have to be missing all of a users posts in a given month.

[11] We include a full 12 months before treatment to provide confidence that our assumption on parallel trends is satisfied in the pre-period. We restrict our analysis to 6 months after the introduction of the News tab, as Reddit continued to update the mobile applications, and we are most confident in the parallel trend assumption during this shorter window following the event. If we extend the analysis to include a full 12 months, the results are similar with the exception of a rise in non-news posts on Android devices.

[12] In our sample of users, over 97% of all posts in communities featured in the News tab were comments rather than original submissions.

4.1. Inferring device type

A limitation of the Baumgartner et al. (2020) data relative to the proprietary data collected by the platform is that we only observe publicly available information, which does not include the device a user was using when making a post. As a result, we must infer device type from posts on the platform. To do so, we consider the subset of users who have posted in the RedditMobile community, which is an official Reddit community for announcements, discussion, and feedback on the official Reddit mobile apps. When posting in this community, users are often posting feedback about the mobile apps and typically include explicit tags about the device and version of the mobile app they are giving feedback on (Figure 2). We infer user device using the following procedure. First, if the user tagged a particular operating system in their post we assign their device accordingly. Second, if the user has tagged their operating system on the community through author 'flair' (for example, the first post in Figure 2 has tagged iOS 14 as their author flair), we assign them to that device. This procedure allowed us to identify 13,710 Android users and 12,419 iOS users. There were an additional 247 users who authored posts that would have been classified as both Android and iOS devices, and these users are excluded from all analyses.

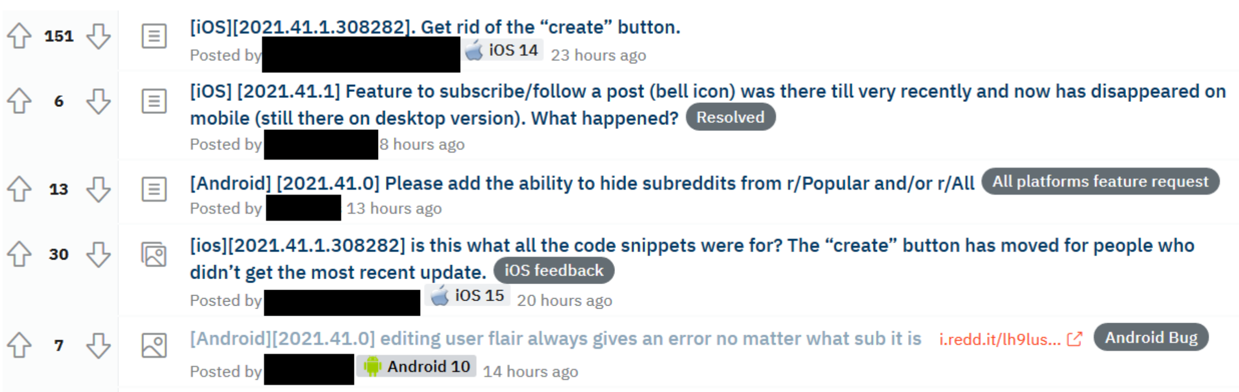


Figure 2 Screenshot of Reddit Mobile feed use to identify user devices

The process of inferring device operating systems limits our sample substantially. As a result, we include all users who have posted on the RedditMobile community rather than only those posting before the News tab was introduced. The primary risk of inferring device type from posts after the News tab was introduced is a bias if users select devices based on this intervention, but we believe this is unlikely to be driving our results.[13] To mitigate

[13] When the News tab was announced, Reddit administrators were explicit that they intended to make this feature available across all devices which should mitigate switching immediately following the release. The announcement

concerns over selective switching, we exclude the small number of authors whose device could be inferred from posts that discuss the News tab explicitly. A more likely issue is device switching that is independent of the Reddit News tab. This should bias our estimates of engagement toward zero so long as the News tab did not induce some users to engage less with news related communities.

Table 2 shows summary stats for users who posted any comment during the period from June 2017 to December 2018 and the subset of these users that we inferred a device. It is worth noting that this sample is highly engaged relative to the universe of Reddit users. This is not surprising given their participation in the RedditMobile community demonstrates their interest in improving and providing feedback on the Reddit mobile applications. While this observation makes generalizing the results of our results to less engaged users more difficult, understanding the impacts of the News tab on highly engaged users is of direct policy and managerial relevance. These users are highly engaged with the platform, and with news related content, so policymakers and managers may be especially interested in the effects of the news feed on the news diets and engagement of these users.

4.2. Communities of interest

The News tab includes 54 communities (subreddits) that are structured into 8 higher-level categories of news.[14] In this study we aggregate engagement to the category level and focus on heterogeneity along news categories rather than individual communities. We do this because the News tab is structured around these categories and the smaller number of categories facilitates comparisons of heterogeneous effects.

We exclude a handful of communities due to concerns about the common trend assumption. First, we exclude technology communities that specifically reference Apple or Google as we are conditioning on users having an Apple or Android device and expect these users to have different engagement patterns on these communities. Second, we exclude all communities in the Crypto category. This is because of a large increase in traffic in late 2017, which resulted

referenced specific plans for availability on desktop and a top comment from an administrator stated the intention to make this available across all platforms (`https://www.reddit.com/r/announcements/comments/8sth30/extra_extra_were_launching_a_news_tab_as_a_beta/e12auz7`). As it became evident that this feature was not planned to be released on Android, selective switching is more plausible, though we find it unlikely that a substantial share of our sample is choosing a smartphone operating system because of this particular Reddit feature.

[14] When Reddit launched the News tab in 2018, the list of communities that were referenced were not made public. To approximate the list of communities that are promoted by the News tab we consider the communities that are present as of August 2021.

	Sample		All Users	
Total Posts	865.619	(15.396)	92.462	(0.175)
Total News	65.363	(2.956)	9.273	(0.030)
Any News	0.599	(0.004)	0.191	(0.000)
Any US World	0.341	(0.004)	0.078	(0.000)
Any Politics	0.169	(0.003)	0.042	(0.000)
Any Technology	0.225	(0.003)	0.032	(0.000)
Any Science	0.188	(0.003)	0.031	(0.000)
Any Sports	0.209	(0.003)	0.067	(0.000)
Any Gaming	0.284	(0.004)	0.051	(0.000)
Any Entertainment	0.276	(0.003)	0.058	(0.000)
Any Business	0.023	(0.001)	0.005	(0.000)

Table 2 Sample Selection

Summary statistics for the sample of users in our study and all users who ever commented on Reddit during the study period. We first aggregate to the user level and then aggregate across users. This table restricts to users who have at least one comment in the study period to ensure the only difference in selection criteria was that we inferred a device for users in the group labeled "Sample". This results in the values in this table being larger than the values in Table 1.

in differential engagement by iOS and Android users. In the end, we focus on the following 8 categories of news: US/World, Politics, Technology, Science, Sports, Business, Gaming, and Entertainment.

4.3. Empirical strategy

We estimate the effect of the News tab on Reddit activity using a difference-in-differences design that makes a common trends assumptions. Formally, we model outcomes Y_{it} using a two-way fixed effects panel regression model

$$Y_{it} = \alpha_i + \lambda_t + \tau \text{Post}_t D_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is the outcome of interest, D_i is an indicator equal to one if user i has an iOS device, Post_t is an indicator for the post-treatment period, and α_i (λ_t) represent unobserved individual (time) fixed effects. Identification of this model comes from a common trends assumption that assumes, absent the introduction of the News tab, the average outcome for iOS and Android users would have followed the same trend over time (Abadie and Cattaneo 2018).

In addition to average effects, we study dynamic treatment effects by estimating event-study models of the form

$$Y_{it} = \alpha_i + \lambda_t + \tau_t D_i + \varepsilon_{it}. \tag{2}$$

We then can interpret τ_t as the average treatment effect of the News tab on iOS users in period t to understand how the treatment effect varies over time. In addition, this specification forms the basis for our test of pre-trends discussed in more detail in the following section. All statistical inference on estimates of Equation 1 and 2 use cluster robust standard errors clustered at the user level (Liang and Zeger 1986).

Before estimating Equations 1 and 2 we perform a Coarsened Exact Matching (CEM) procedure that accounts for imbalance in baseline engagement in the pre-period through re-weighting (Iacus et al. 2012, Gertler et al. 2016). To give more detail, in the first 6 months of the pre-period we create indicators equal to one if a user posted in any community (news or non-news) during the month. We then match users based on these 6 covariates, and form weights following (Iacus et al. 2012).[15] Full details of the matching procedure is explained in Appendix A. This weakens the identification assumption required, as we now only need common trends to hold conditional on the covariates used in matching. Results of the analysis without using the CEM weights are shown in Appendix F and the results are largely consistent.

4.4. Testing for pre-trends

To have a causal interpretation, the empirical strategy described in Section 4.3 relies on a common trends assumption. To be explicit, our identifying assumption is that, absent the introduction of the News tab, iOS and Android engagement would have followed the same time trends conditional on pre-treatment covariates used in matching. While this cannot be tested empirically, we can test for common trends in the pre-treatment period that would be consistent with this assumption. To do so, we perform the joint test that pre-treatment coefficients in Equation 2 are equal to zero.

When considering if a user posted in any news related community, we fail to reject the null hypothesis of common pre-trends (p=0.26). Moreover, when looking at specific topics

[15] This procedure is numerically equivalent to subclassification by pre-period engagement in this setting.

we fail to reject the null of common pre-trends at the 5% level in all categories (Figure A3). For the outcome of an indicator of any low-quality post, we fail to reject the null hypotheses of common pre-trends for all 8 categories of news (Figure A4) and the same is true for the high-quality post analysis (Figure A5). Similarly, we fail to reject the null hypothesis of common pre-trends for all outcomes in the analysis of engagement diversity. That none of the tests reject at the 5% level gives us confidence that common pre-trends is satisfied in our sample.

5. Results

5.1. Effect on engagement quantity

To study the impact of the News tab on engagement with news related communities, we first estimate Equation 1 where the outcome is an indicator equal to one if a user posts on any community suggested by the News tab. In aggregate, we find the News tab increases the probability of posting on any news related community by 3.3% (0.54 percentage points, p=0.04).

This aggregate view, however, masks substantial variation in effect sizes by the topic of news (Figure 3). Recall there are 8 categories of news included in the News tab (US/World, Politics, Technology, Business, Science, Sports, Gaming, and Entertainment) and we can estimate the effect of the News tab on the monthly engagement probability for each category. Figure 3 plots the estimates of the average treatment effect on iOS users of the News tab on engagement with each of the 8 news categories. In all categories, the treatment effect point estimates are positive or statistically indistinguishable from 0. This suggests the News tab increases total engagement, but this increase is concentrated in a subset of news categories. There is a statistically significant treatment effect for the Politics (p<0.001), Technology (p<0.001), and Business (p<0.001) categories.

Recall these effect sizes represent the share of individuals induced by the News tab to post in each particular community in a given month. Baseline engagement rates are relatively low in this sample, with on average only 3.3% of iOS users posting in the Politics community in the year leading up to the introduction of the News tab. Therefore, a treatment effect of 0.72 percentage points represents a 21.8% increase in the *monthly* share of iOS users who post in the Politics community. There is also a 15.7% increase in the share posting in Technology communities, and a 80.5% increase in the share posting in Business communities.

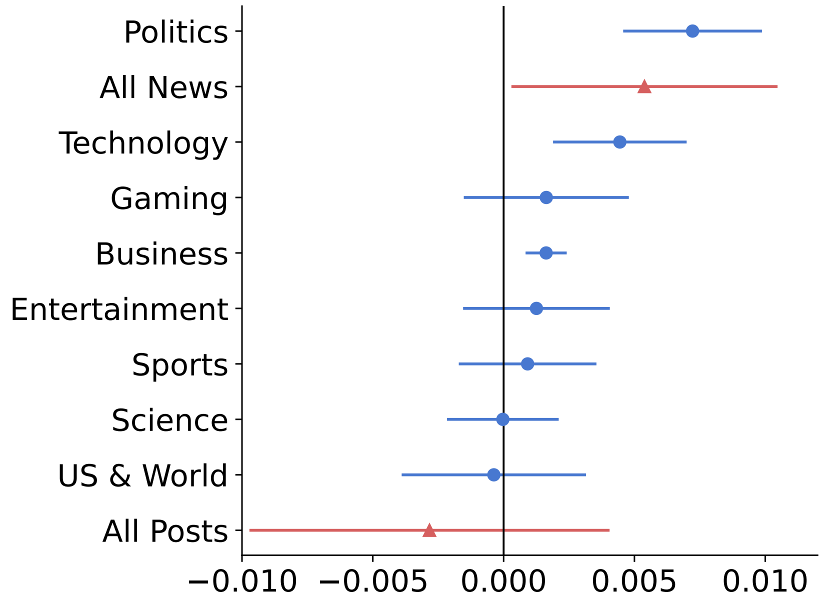
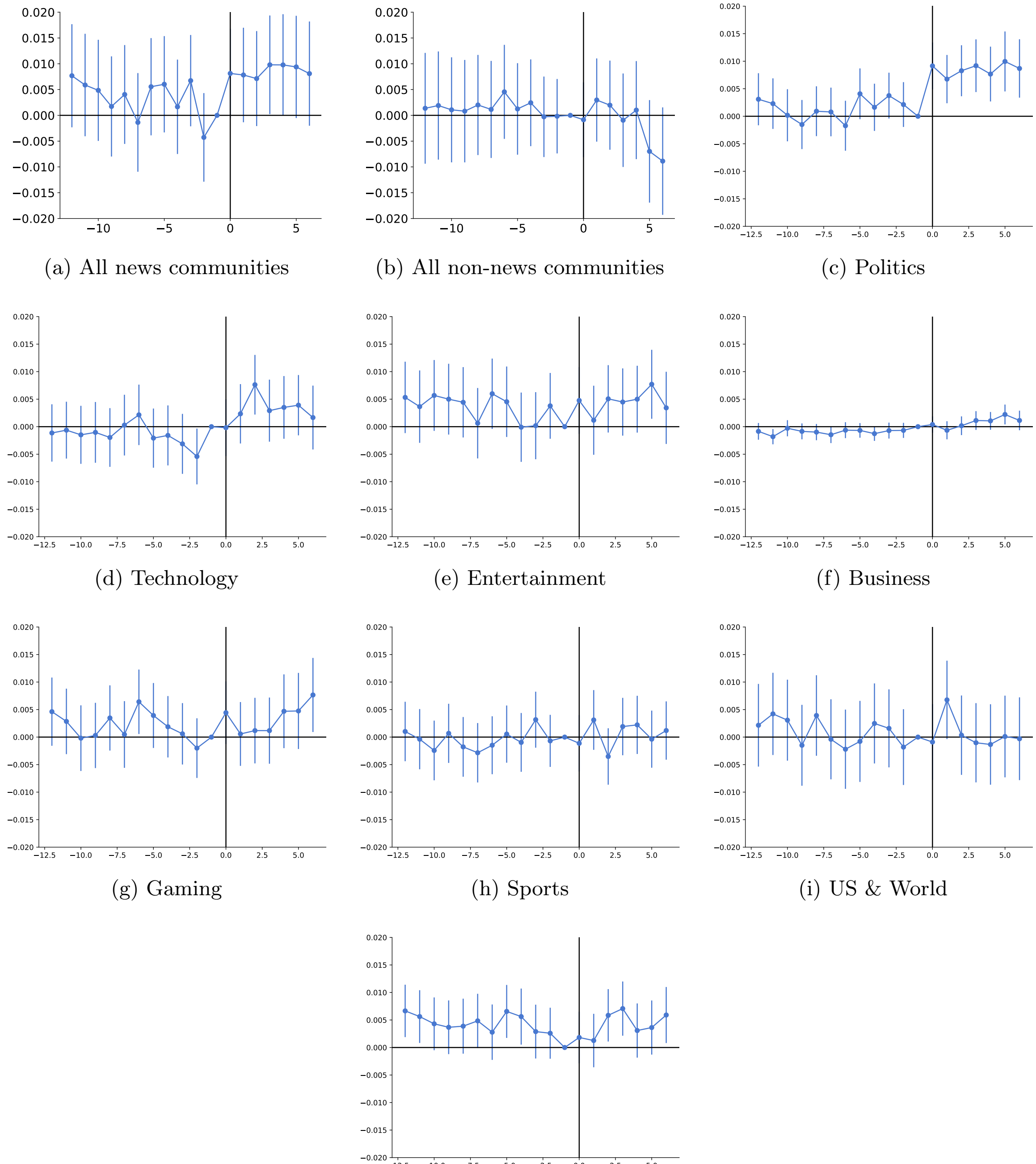


Figure 3 Treatment effect estimates on probability of posting

Coefficients from estimates of Equation 1 on an indicator if a user posted in the community in a given month. Each red point represents the estimated average treatment effect of the News tab on the probability of engagement for the 8 categories of news. The red triangles represent the treatment effect of the News tab on the probability of engagement with all 8 categories of news combined and all subreddits combined. Bars represent 95% confidence intervals.

We can also estimate treatment effect dynamics by estimating Equation 2, again with the outcome being an indicator equal to one if a user posts in the relevant communities in a given month (Figure 4). These results serve two purposes. First, they show the treatment effect dynamics and that the treatment effects persist for some time following the intervention, though there is some variation over time. Second, this figure allows us to visualize the test for pre-trends we discussed in Section 4.4. For all figures, the pre-period confidence intervals include zero in nearly all months, consistent with common pre-trends. For a subset of the categories, we see examples of pre-periods where 0 is not included in the confidence intervals in a handful of months. In these cases, we emphasize that with 12 pre-periods we would expect there to be some rejections in individual months under the null hypothesis of common pre-trends. We therefore emphasize that the more appropriate statistical test is that these pre-trends are jointly zero, as it accounts for the multiple pre-periods and the correlation among pre-period estimates. As mentioned above, we fail to reject common pre-trends using the joint test in all categories at the 5% level.



(a) All news communities (b) All non-news communities (c) Politics

(d) Technology (e) Entertainment (f) Business

(g) Gaming (h) Sports (i) US & World

(j) Science

Figure 4 Dynamic treatment effect estimates on probability of posting

Dynamic treatment effect estimates on probability of posting in community, estimated using Equation 2. Bars represent 95% confidence intervals.

The above analysis focuses on the extensive margin of engagement, showing that the News tab induces additional iOS users to post on news related communities relative to Android users. Next, we consider how the News tab impacts the intensive margin by estimating

Equation 1 on a series of additional outcomes. Specifically, we estimate Equation 1 where the outcome is a series of indicators equal to one if total engagement in a category is above a threshold ranging from 0 to 50. This estimates the treatment effect for iOS users on the probability of a user having more posts in a month than the threshold.[16] The results of this analysis are shown in Figure A7. There is a clear pattern, where the absolute treatment effects of the News tab are largest for lower thresholds suggesting the News tab induces users to post a few times in a month rather than inducing users to become heavy users.

5.2. Effect by domain

Focusing on the politics community, we now investigate the effect of the News tab on the political slant of the news publishers that users engage with. In particular, we consider heterogeneous effects on engagement with news articles by publishers of varying political slant. We operationalize publisher political slant following Robertson et al. (2018), which is explained in more detail in Appendix B.

The vast majority of threads in the news communities are started by someone sharing an article related to the community's topic. For this analysis, we drop the 9.5% of posts that link to non-news domains, which primarily consists of links to general discussion threads on Reddit. We match publisher domains to the domain political slant measures of Robertson et al. (2018), who calculate domain level political slant of 19,022 of the most popular domains. Additional details about these data can be found in Appendix B. Over 95% of the remaining posts in the politics community by our sample were on a thread started by a link to a publisher domain contained in the Robertson et al. (2018) slant data. We then partition the publishers into five equally sized bins based on their slant. The majority of engagement is on articles from left-leaning publishers, with less than 20% of posts on threads initiated by articles from right-leaning outlets and over half of posts on threads initiated by articles from left-leaning outlets (Figure 5). This appears to be primarily demand driven rather than supply, as the share of threads (rather than posts) is more evenly distributed across publishers of various political slants.

Next we investigate how the News tab differentially impacts engagement on the various partitions. We find that the News tab significantly increases engagement for left-leaning

[16] A natural outcome for the extensive margin analysis would be the log-transformed number of posts, though the log-transformation suffers two pitfalls. First, given the sparsity of our dataset the arbitrary choice of how to handle zeros would be consequential. Second, and more importantly, common trends in the extensive margin (probability of posting) is inconsistent with common trends in the log-transformed outcome unless we make further strong assumptions that are rejected in the data.

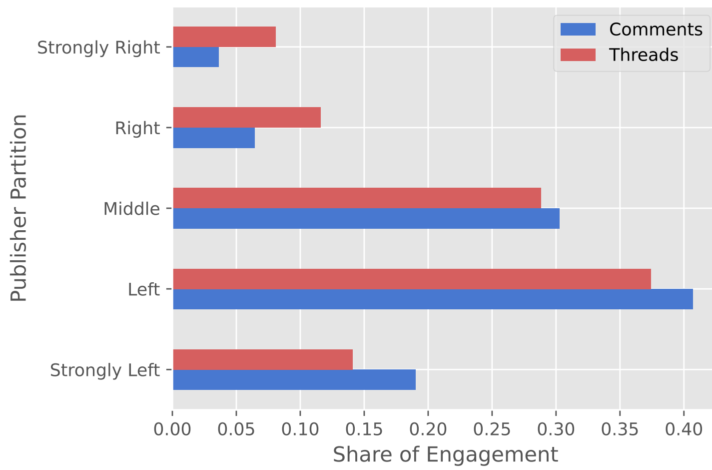


Figure 5 **Distribution of posts in hard-news communities across domain slant partitions**

Within the Politics community, this figures plots the share of engagement on posts and the share of threads about an article by publishers across the political spectrum.

and moderate outlets. The increase among conservative-leaning publishers are statistically indistinguishable from zero (Figure 6).

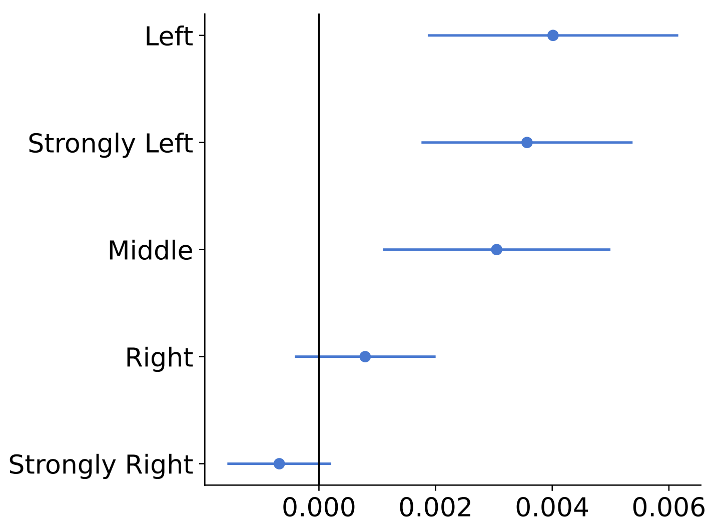


Figure 6 **Treatment effects on probability of posting on a thread by publisher political slant**

This figure plots estimates of Equation 1 where the outcome is an indicator if the user posts on a thread in the politics community discussing an article from a publisher within each slant partition.

5.3. Effect on individual engagement diversity

Turning toward the diversity of engagement, we find that the News tab induces individuals to engage with more diverse content. This is true both among the topics included in the News tab and among publisher slant partitions within the politics community (Table 3). This result is robust to various definitions of individual engagement diversity, as we see increases in diversity as measured by the Shannon Entropy (Shannon 1948, Holtz et al. 2020) of engagement shares, the Herfindahl-Hirschman index[17], and breadth (i.e. the number of categories the user engaged with). Full details of the diversity measures can be found in Appendix C.

We find that the Shannon Entropy of diversity across categories of news included in the News tab increased by 8.4% and the News tab increased the Shannon Entropy of diversity across publishers from different political slants by 15.9% (see Appendix C for event studies of diversity measures). To try and contextualize the magnitude of this increase in diversity, we calculated what share of the maximum possible increase in diversity we observed from the News tab. Specifically, for iOS users in the post-treatment period, we calculated the maximum possible Shannon Entropy of engagement given the total engagement amount and estimated Equation 1 on this new outcome. This provides an upper bound on the potential increase in engagement diversity holding total engagement fixed. We find that the increase in engagement caused by the News tab represents 2.7% of the maximum increase for diversity across news categories and 12.2% of the maximum increase for diversity across publishers of varying political slant. Recall this is relative to a best-case benchmark that would require a severe change in engagement patterns to achieve. Therefore, we view this as a meaningful increase in the diversity of news users engage with, particularly for diversity across partitions of political slant.

5.4. Effect on engagement quality

In addition to the quantity and diversity of engagement, we also can estimate the effect of the News tab on the quality of engagement through a number of different measures. First, we consider the relative number of upvotes and downvotes by participants in the communities. Recall that votes on Reddit are intended to be a mechanism to signal if a comment or submission contributes to the conversation or not, which we are interpreting as a signal of

[17] Recall a smaller HHI is associated with more diversity, so the negative treatment effects here are consistent with the News tab increasing diversity.

	News Categories			Political Slant		
	Entropy	HHI	Breadth	Entropy	HHI	Breadth
Post × iOS	0.0044***	-0.0025***	0.0167***	0.0023**	-0.0015***	0.0107***
	(0.0015)	(0.0009)	(0.0056)	(0.0010)	(0.0006)	(0.0033)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
N	496451	496451	496451	496451	496451	496451

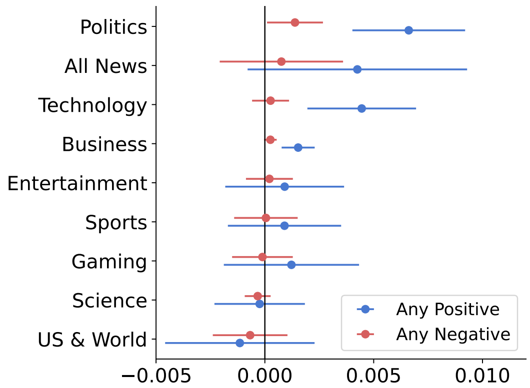
*$p < 0.1$; **$p < 0.05$, ***$p < 0.01$

Table 3 Treatment effects on engagement diversity.

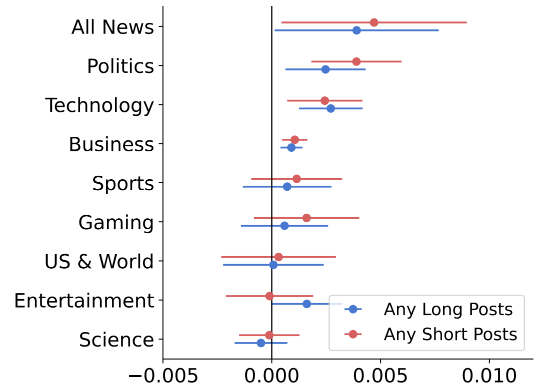
Estimates of Equation 1 for the various measures of individual engagement diversity. These are estimated both for diversity across the 8 categories of news promoted in the News tab and the partitions of political slant within the politics community.

post quality as judged by the participants in the community. Therefore, we again estimate Equation 1 with an indicator if any of an author's posts were 'negative' or 'positive'. Here, we define a negative post to be a comment that received more downvotes than upvotes and a positive post to be a comment that received more upvotes than downvotes. We also estimate treatment effects on an indicator if an author posted any long or short posts in a month, where a long (short) post is defined as a post with more (fewer) words than the 75th (25th) percentile of comments in the pre-period. Finally, we estimate treatment effects on an indicator if a user posted any positive or negative sentiment posts in a month, operationalized through the VADER algorithm (Hutto and Gilbert 2014).

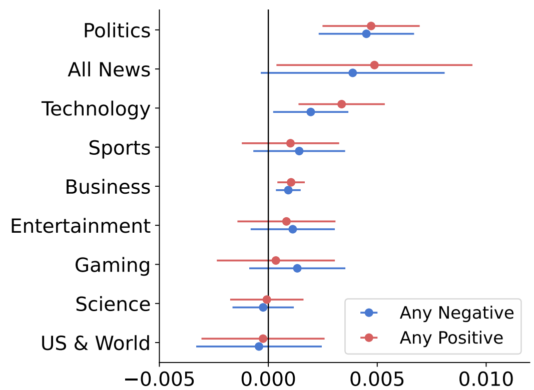
Results of these analyses are shown in Figure 7. We find that for all news communities, there is an increase in the share of users contributing high quality posts measured by post length (p=0.04) and post sentiment (p=0.03) and an increase in the share of users contributing low quality posts measured by post length (p=0.03) and post sentiment (p=0.07). The results are consistent for quality as measured by voting, but statistically indistinguishable from zero. For the politics community, which saw the largest influx of new users, we saw a significant increase in both high and low quality engagement across all quality measures. Although the relative increase in users posting a low quality comment as measured through votes and post length is larger than those posting high quality comments, we are unable to distinguish the two statistically. Taken together, these results suggest that the composition of posts does not meaningfully change following the influx of new users.



(a) Post score



(b) Post length



(c) Post sentiment

Figure 7 Treatment effect on post quality measures

Coefficients from estimates of Equation 1 on an indicator if a user posted a high or low quality post in a given month measured by (a) post votes, (b) post length, and (c) post sentiment. Each point represents the estimated average treatment effect of the News tab on the probability of posting a positive or negative comment for the 8 categories of news. Bars represent 95% confidence intervals.

6. Mechanisms and robustness of the conclusions

As shown in Section 5, there is substantial heterogeneity in the impact of the News tab on engagement with the various categories of news, with the Politics community seeing the largest increase in engagement. A potential explanation for this heterogeneity could be a result of the design of the News tab itself. While the News tab does have subsections for each of the 8 different categories of news content, the feed individuals first interact with aggregates popular content from across all categories of news content (Figure 1). It is plausible that users are more likely to engage with content promoted on this page. To evaluate this hypothesis, we create a monthly index of popularity for each news category and predict monthly treatment effect estimates with this index.[18] We find that this measure of popularity is correlated with the monthly treatment effect estimates on the probability of posting (Table 4). While this should not be interpreted causally, as there is simultaneity between popularity and treatment effects, this correlational evidence is consistent with the hypothesis that the heterogeneous effects of the News tab are a result of the underlying popularity of the different categories. An important implication of this hypothesis is that the choice of the News tab sorting algorithm is critical. If this hypothesis were correct, it would mean promoting content from a different category of news would increase engagement with the promoted category. More important, it would also suggest an algorithm that favored content slanted towards a particular political ideology would increase engagement with this content (e.g. Huszár et al. (2021)), further highlighting the importance of the choice of algorithm in influencing the content individuals see and ultimately engage with.

	(1)
Popularity	0.049
	(0.010)
Constant	0.003
	(0.000)
p-value	<0.001
Obs	56
Adj. R^2	0.232
F-stat	21.827

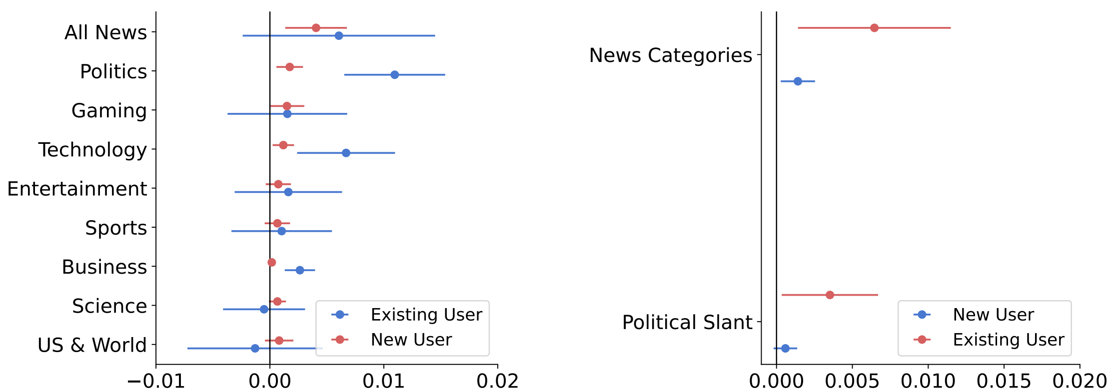
Table 4 Correlation in community popularity and treatment effects

Coefficients from the regression of monthly treatment effect estimate on community popularity.

In addition to understanding the heterogeneity in treatment effects across news categories, we can also better understand the mechanism behind the increase in engagement and engagement diversity by studying who is most affected by the News tab. To do so, we estimate treatment effects on engagement quantity and diversity separately for individuals who

[18] Unfortunately, historical data on which posts were promoted are unavailable. Therefore, we scrape a Reddit page that shows the most popular posts from a given day. See `https://www.reddit.com/r/changelog/comments/k663qy/introducing_rereddit_go_back_in_time_to_see_top/` for a description of this page. We then define the popularity index as the monthly average share of posts in the top 50 most popular news posts that came from each category of news.

engaged with Reddit in the pre-period (existing users) and those who had not engaged with Reddit in the pre-period (new users).[19] This heterogeneity analysis is displayed in Figure 8. We find that both groups are more likely to engage with News content as a result of the News tab, but the treatment effects are significantly larger for existing users in the Politics, Technology, and Business categories. We also find larger treatment effects on the diversity of engagement for existing users across news categories (p=0.06) and across political slant partitions (p=0.08), though the smaller sample sizes lead these differences to be statistically significant only at the 10% level. Nonetheless, this again suggests that the effects of the News tab work by encouraging existing users to engage with more news related content and a more diverse set of content.



(a) Any posts

(b) Diversity

Figure 8 Heterogeneous effects by baseline engagement

This Figure plots estimates of Equation 1 separately for groups of users who commented on Reddit in the pre-period (Existing User) and for those who did not comment on Reddit in the pre-period (New User). The outcome variables are (a) an indicator if the user posted any comments in the relevant communities and (b) diversity measures across the 8 categories of news and across the political slant partitions.

Finally, we conduct a placebo test to rule out a competing hypothesis that could explain why the largest treatment effects are in the Politics category. We could be concerned that the News tab was introduced in the months leading up to a U.S. midterm election. To address the concern that the results are confounded by the election, we estimated the effect of the News tab on placebo communities that are focused on discussing politics but were not included in

[19] By new user, we mean users without prior posts. That is, the user could have had an account in the pre-period, but they did not make any comments in the pre-period.

the News tab. We find precise null effects for these communities suggesting that the effect we find for the Politics community included in the News tab is in fact a result of the News tab and not a result of the introduction of the News tab coinciding with an election cycle (Figure 9).

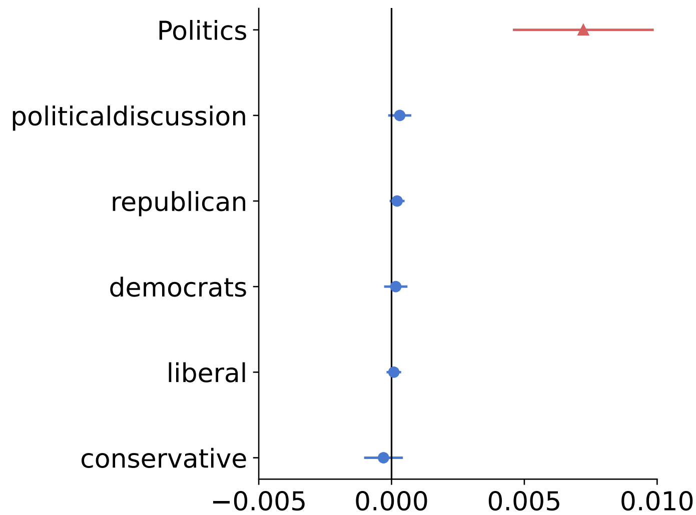


Figure 9 **Election Placebo Tests**

This Figure displays results of a placebo test on political communities not included in the News tab (blue) compared to the Politics community included in the News tab (red). We find no treatment effect on communities excluded from the News tab suggesting the effect is not driven by the 2018 midterm election.

7. Discussion and conclusion

We find that the News tab increased engagement with news related content and the marginal content induced by the News tab was of similar quality to existing content. In addition, the News tab increases the diversity of engagement across news categories and content from outlets with different political leanings.

This study, however, is not without limitations. First, our analysis relies on publicly observed information which requires us to limit our sample to individuals who reveal their device through the RedditMobile community. As discussed, the sample for which we could infer the device was a more engaged sample than the universe of Reddit users. Therefore, we must be cautious when generalizing these results to external populations given we are studying the effects of the News tab on an engaged set of users. That said, we believe this limitation does not impact the internal validity of our results, which still have important managerial and policy implications given the importance of this highly engaged sample. From a policy perspective, given these users are more likely to engage with news related content, understanding the effects of the non-personalized news feed on these users' news diets is particularly important. Moreover, these users are likely particularly valuable to the firm given their above average engagement, so understanding how this feature impacts these users' engagement is also of significant managerial importance. Another limitation of this study, given our reliance on publicly observable data, is we are only able to measure engagement through posting to the platform. Therefore, we are unable to study the robustness of our conclusions to other engagement measures such as time spent viewing content and clicks.

Our findings have several takeaways. First, we highlight the heterogeneous increase in engagement that was induced by the News tab. Not all communities saw significant increases in engagement with only Politics, Technology, and Business related communities seeing significant increases. In addition, we find heterogeneity based on user type with increases concentrated in existing users. We also found the engagement induced by the News tab was similar in quality to existing engagement, so concerns around a deterioration in quality following an influx of new users appear unfounded, a finding consistent with prior literature (Kiene et al. 2016).

In addition, our findings on the diversity of engagement have important policy and social implications. Previous work has found that personalized news feed algorithms and personalized recommendations have led to filter bubbles and decreased content consumption diversity (Bakshy et al. 2015, Claussen et al. 2019, Allcott et al. 2020, Levy 2021, Holtz et al. 2020). Moreover, these studies often find a tension between engagement diversity and engagement quantity. We demonstrate that augmenting personalized feed algorithms with a supplementary non-personalized feed can increase both engagement with the featured communities and engagement diversity. This is true both for engagement among different categories of news in addition to the diversity of engagement among articles across the political spectrum. From a managerial perspective, more diverse engagement has been shown to positively impact user retention (Anderson et al. 2020). From a policy perspective, users consuming and engaging with a more diverse set of political viewpoints has important positive implications for civic life (Sunstein 2003). This suggests that non-personalized supplementary news feeds can be an important tool in mitigating algorithmic filter bubbles.

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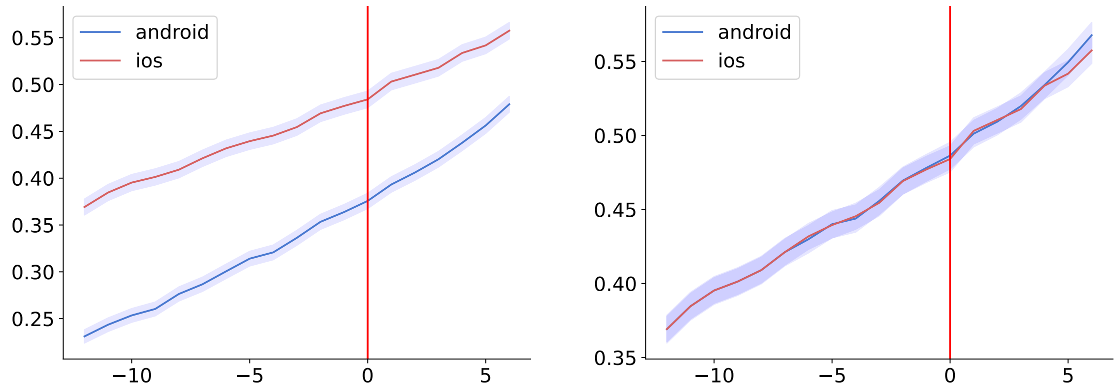
Appendix A Matching Procedure

Our analysis of the impact of the News tab relies on a common trends assumption to have a causal interpretation. Non-weighted engagement trends, i.e. those estimating Equation 2 without the Coarsened Exact Matching (CEM) procedure are largely consistent with this hypothesis with one notable exception where the probability of posting on any non-news community shows a clear pre-trend (Figure A10). We use the CEM procedure outlined in Iacus et al. (2012) to mitigate this imbalance.

There are 12 pre-treatment periods in our analysis, and we match on the first 6 of these pre-treatment periods, holding out the following 6 to provide further evidence our common trends assumption is plausible. We define $X_i = (x_{i,-12}, \ldots, x_{i,-7})'$ as a vector of dummy variables $x_{i,t}$ equal to one if user i made any posts (on any community, not just news) in period t. We then generate weights from CEM following Iacus et al. (2012). Given the relatively low-dimensionality of this matching exercise we are able to find exact matches and this is equivalent to subclassification. We then use these weights in our difference-in-differences framework, which requires the assumption of common trends conditional on the covariates used in matching. In other words, we assume that iOS engagement trends would have followed Android engagement trends absent the introduction of the News tab, *conditional* on X_i.

To demonstrate the effectiveness of the matching procedure, we can plot the unweighted and weighted probability of posting any post on Reddit over time by treatment group (Figure A1). While difficult to see in the raw time series figure below, there is clear evidence of differential pre-trends between iOS and Android users (Figure A10). Re-weighting eliminates this imbalance and it does so even in the periods before treatment that are not used in weighting.



(a) Unweighted (b) Weighted

Figure A1 Probability of post on any Reddit community by treatment group

Appendix B Data on domain political slant

We obtain political slant by domain using Robertson et al. (2018). To generate this score, Robertson et al. (2018) collect recent tweets containing links from known Democrats and Republicans. The slant measure is then calculated as the difference in the probability of a sharing a domain conditioned on being republican who has shared at least one domain less the same conditional probability for democrats, normalized to be between -1 and 1. Formally, the slant measure is defined as

$$\text{bias-score}(i) = \frac{\frac{r_i}{\sum_{j\in I} r_j} - \frac{d_i}{\sum_{j\in I} d_j}}{\frac{r_i}{\sum_{j\in I} r_j} + \frac{d_i}{\sum_{j\in I} d_j}}$$

where r_j (d_j) is the number of unique Republicans (Democrats) who shared domain j and I is the set of all domains. This measure is equal to 0 if shared by equal shares of Republicans and Democrats and equal to 1 (-1) if it was shared only by Republicans (Democrats). Robertson et al. (2018) demonstrate their measure of domain slant agrees with several existing measures of publisher slant (Bakshy et al. 2015, Budak et al. 2016)

Appendix C Measures of information diversity

Our measures of engagement diversity first partitions engagement into K bins based on either the category of news community or the political slant of the publisher within hard-news communities as calculated in Robertson et al. (2018). We then operationalize the diversity of engagement following Holtz et al. (2020), measuring individual-level engagement diversity using Shannon entropy (Shannon 1948). The Shannon entropy of user i's engagement is defined as

$$id_i = -\sum_{k=1}^{K} s_{ki} \ln(s_{ki}), \tag{A3}$$

where s_{ki} is the share of user i's posts on a thread based on an article from publishers in partition $k \in \{1, \ldots, K\}$. If $s_{ki} = 0$, the partition's contribution to the Shannon entropy is zero which implies users who do not engage with any posts have $id_i = 0$ (Holtz et al. 2020).

We also operationalize engagement diversity using the Herfindahl–Hirschman Index (HHI) (Rhoades 1993). This measure is defined as the sum of squared engagement shares:

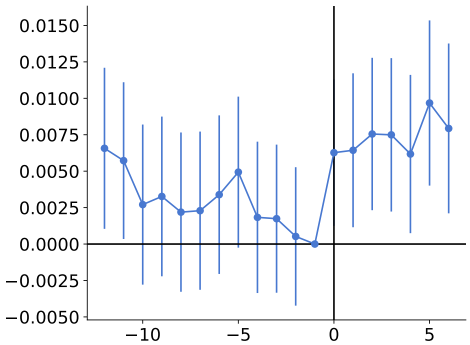
$$\mathrm{HHI}_i = \sum_{k=1}^{K} s_{ki}^2.$$

When an individual has no consumption in a period, we define the HHI to be equal to one which is equivalent to engaging entirely with content from a single category.

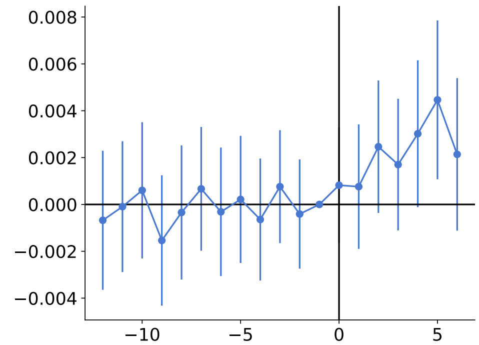
Finally, we also consider engagement breadth as another measure of engagement diversity. Breadth is defined as the number of unique categories the user engaged with in a month:

$$\mathrm{Breadth}_i = \sum_{k=1}^{K} 1[s_{ki} > 0].$$

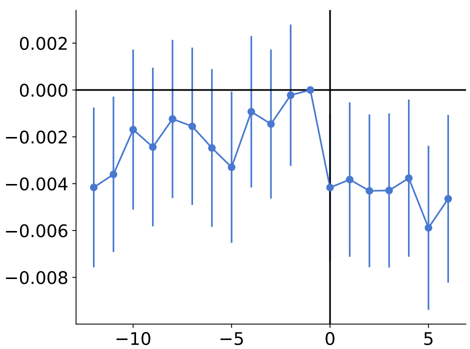
Figure A2 plots event studies for these three diversity measures.



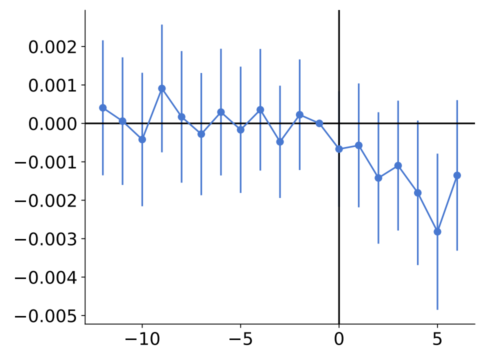
(a) Shannon Entropy: News Categories



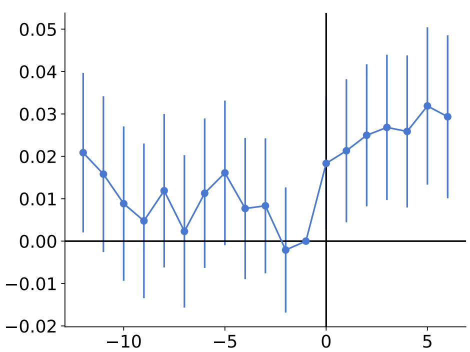
(b) Shannon Entropy: Political Slant



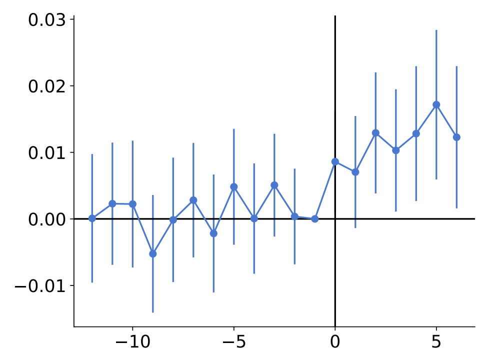
(c) HHI: News Categories



(d) HHI: Political Slant



(e) Breadth: News Categories



(f) Breadth: Political Slant

Figure A2 Individual engagement diversity event studies

Dynamic treatment effect estimates of Equation 2 for individual engagement diversity. Figures A2a, A2c, and A2e plot diversity of engagement across the 8 categories of communities on the news tab. Figures A2b, A2d, and A2f plot engagement diversity across political slant partitions. We plot each of the three diversity measures, Shannon Entropy (Figures A2a and A2b), HHI (Figures A2c and A2d), and breadth (Figures A2e and A2f).

Appendix D Testing for common pre-trends

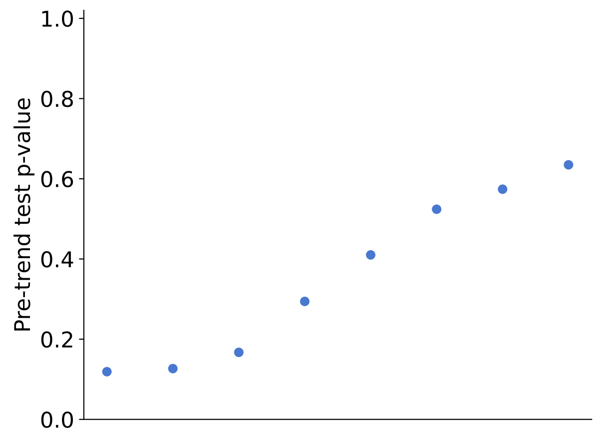


Figure A3 **Common pre-trends p-values for indicator of any post**

Plot of p-values of test of common pre-trends. The test is the joint test that all pre-period treatment effect coefficients in Equation 2 are equal to 0. The p-values are arranged in ascending order.

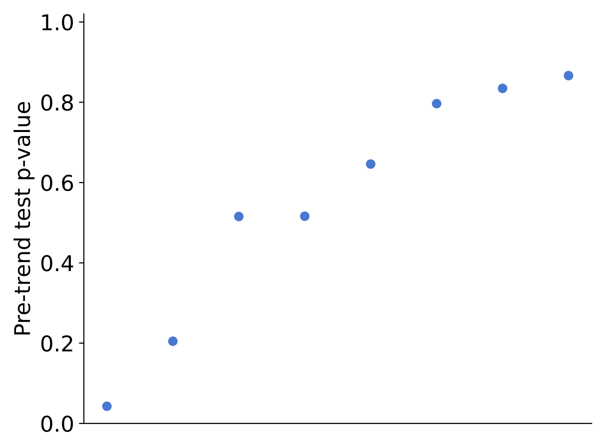


Figure A4 **Common pre-trends p-values for indicator of low quality post**

Plot of p-values of test of common pre-trends. The test is the joint test that all pre-period treatment effect coefficients in Equation 2 are equal to 0. The p-values are arranged in ascending order.

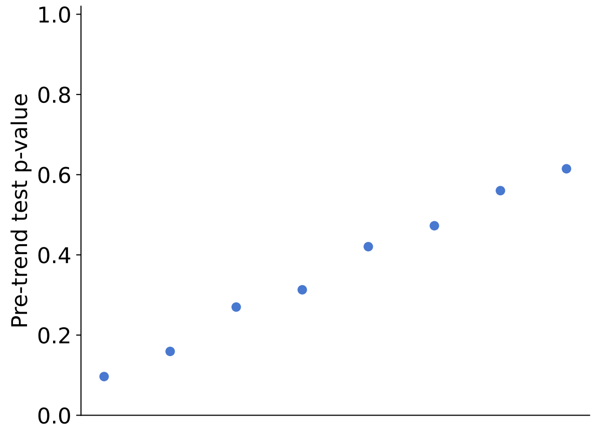


Figure A5 **Common pre-trends p-values for indicator of high quality post**

Plot of p-values of test of common pre-trends. The test is the joint test that all pre-period treatment effect coefficients in Equation 2 are equal to 0. The p-values are arranged in ascending order.

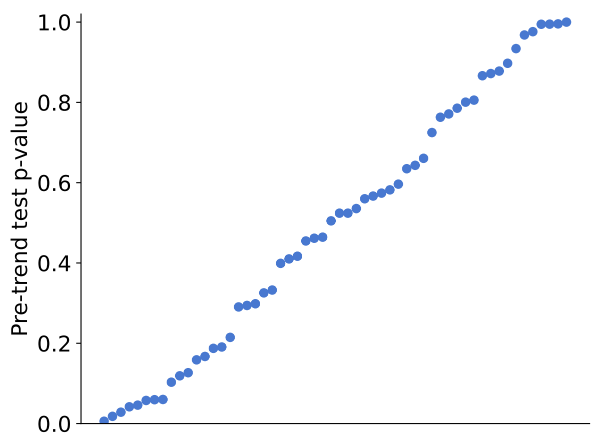
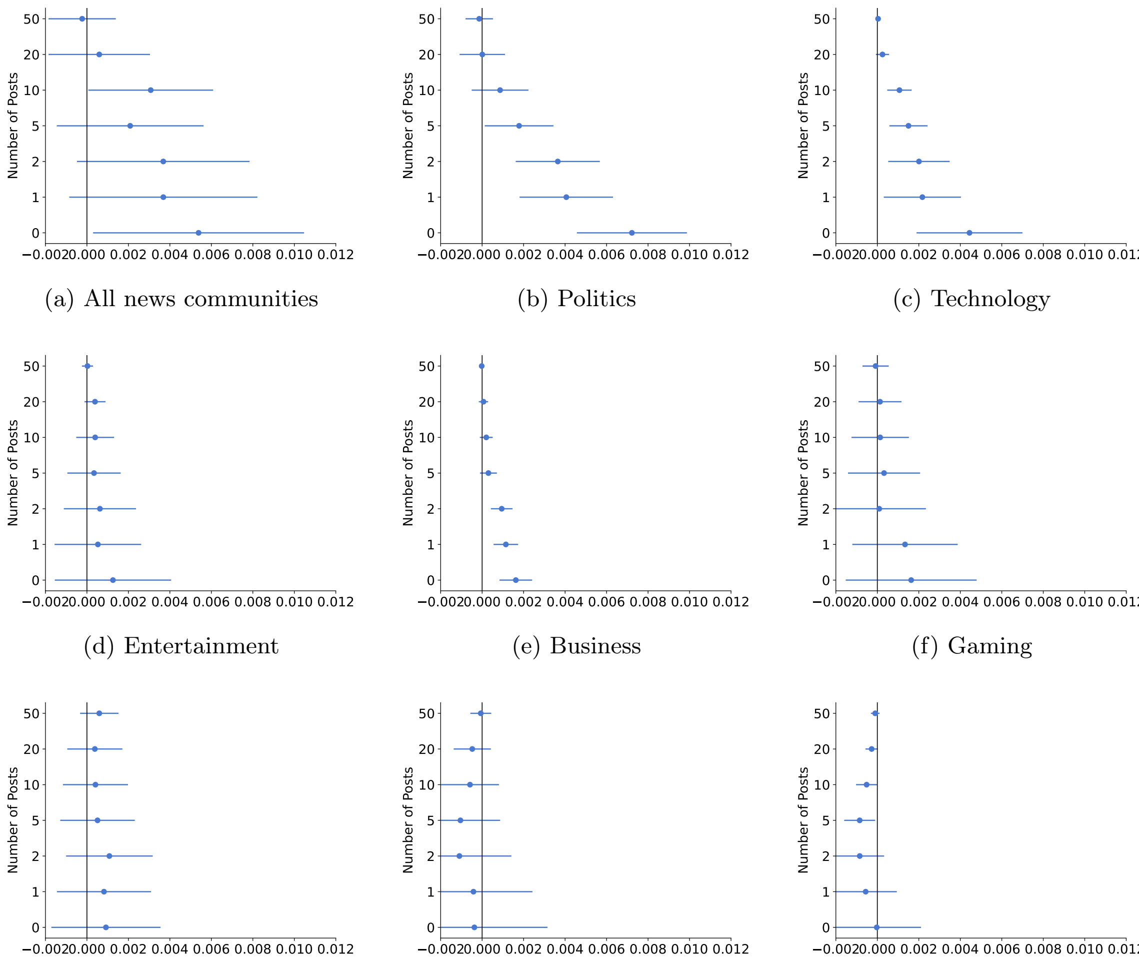


Figure A6 **Common pre-trends p-values for intensive margin analysis**

Plot of p-values of test of common pre-trends. Each point represents the p-value of a joint test that all pre-period treatment effect coefficients in Equation 2 are equal to 0. The figure plots the p-values for all thresholds shown in Figure A7 across all the categories included in the News tab. The p-values are arranged in ascending order.

Appendix E Effect on intensive margin of engagement



(a) All news communities (b) Politics (c) Technology

(d) Entertainment (e) Business (f) Gaming

(g) Sports (h) US & World (i) Science

Figure A7 Treatment effect estimates on probability of posting more than k posts

Each plot shows the treatment effect estimate from Equation 1 where the outcome is an indicator if the user posted more than a threshold posts in a month (within each community). The thresholds are shown on the y-axis. Horizontal bars represent 95% confidence intervals

Appendix F Analyses without CEM weights

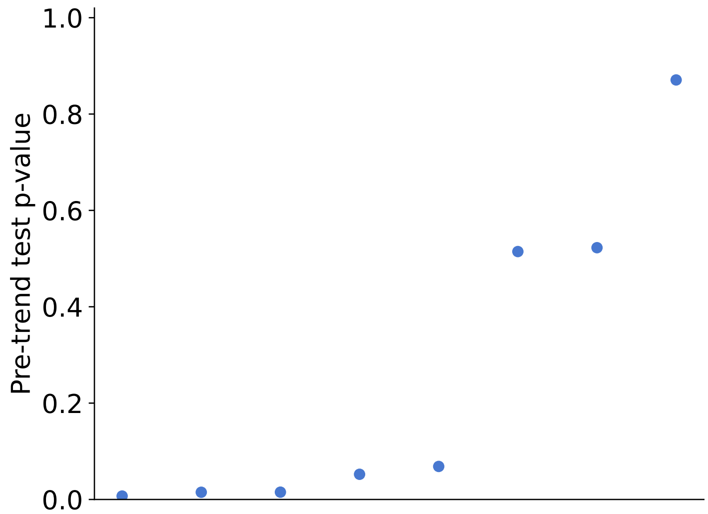


Figure A8 **Common pre-trends p-values**

Plot of p-values of test of common pre-trends without CEM matching. The test is the joint test that all pre-period treatment effect coefficients in Equation 2 are equal to 0.

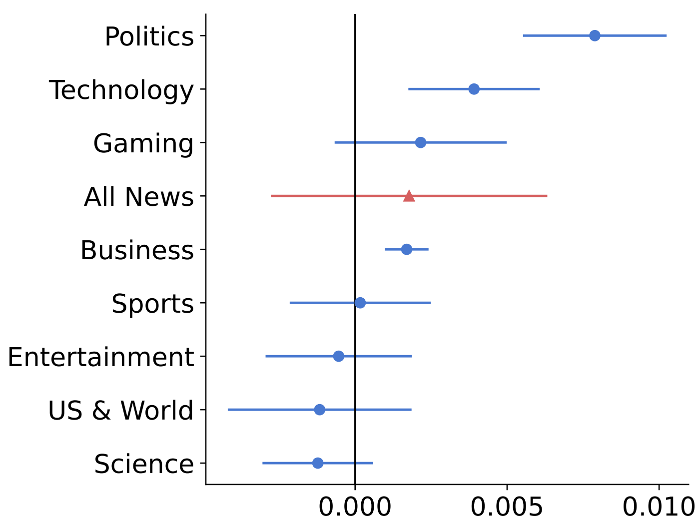
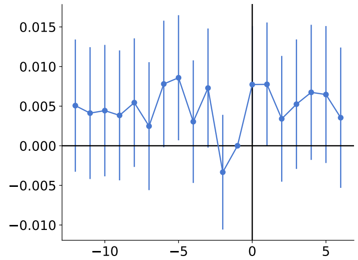
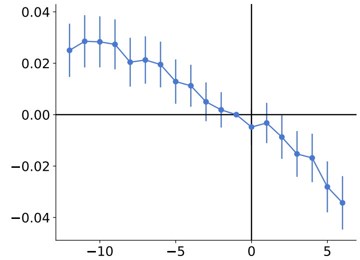


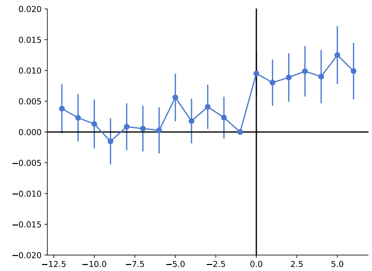
Figure A9 **Treatment effect estimates on probability of posting**



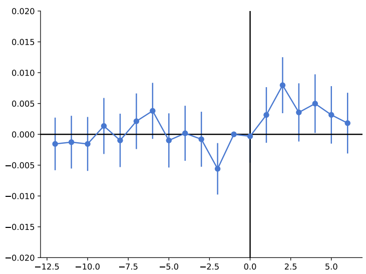
(a) All news communities



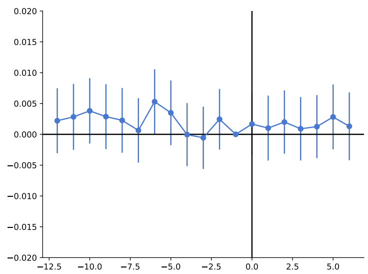
(b) All non-news communities



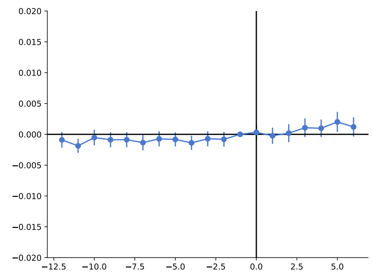
(c) Politics



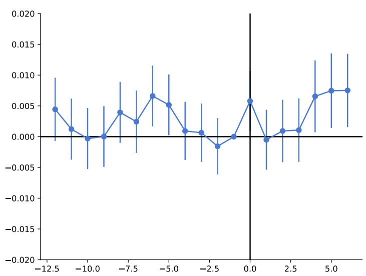
(d) Technology



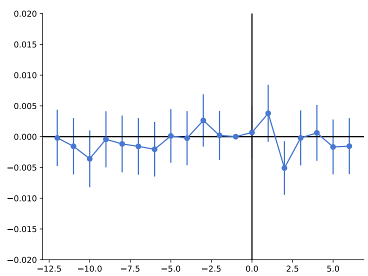
(e) Entertainment



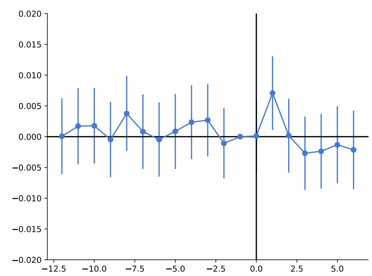
(f) Business



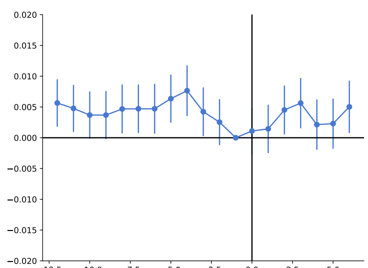
(g) Gaming



(h) Sports



(i) US & World



(j) Science

Figure A10 Dynamic treatment effect estimates on probability of posting

Dynamic treatment effect estimates on probability of posting in community, estimated using Equation 1 without the Coarsened Exact Matching weights.