Weaponizing the Wall: The Role of Sponsored News in Spreading Propaganda on Facebook

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***Abstract*—A large fraction of people today consume most of their news online, and social media platforms like Facebook play a significant role in directing traffic to news articles. While news organizations often use Facebook advertising to drive traffic to their websites, this practice can inadvertently lead to biases in what articles users get exposed to, or worse, could be used as a mechanism for manipulation. In this work, we examine the impact of sponsored news on Facebook on the dissemination of propaganda. Propaganda is a method of persuasion that is frequently employed to advance some sort of goal, such as a personal, political, or business objective. By analyzing more than 17 Million Facebook posts and 6 Million sponsored advertisements gathered over 182 days, we observe that advertisers of all kinds, including politicians, media houses, and commercial corporations, publish thousands of ads/boosted posts every day on Facebook. However, Facebook excludes ads from news organizations from their public ad archive even when their ads talk about politics and social issues, thus putting news organizations in the unique position of publishing paid political opinions without any transparency requirement. The danger is that news organizations or other third-party interest groups can carefully select news articles that drive their points and that look legitimate because ads link to sites of known news organizations. In this paper, we explore *how sponsored news on Facebook can be a powerful tool for spreading propaganda*. We believe the paper will help raise awareness among users about the potential biases in sponsored news and the need to critically evaluate the information they see on Facebook.**

***Index Terms*—Social and Media Analysis, Facebook, Propaganda, Deep Learning**

I. Introduction

In our increasingly interconnected world, the way we consume news has undergone a profound transformation. A significant portion of today's population turns to the internet as its primary source of information, and while online news outlets are experiencing a surge in web traffic, a substantial share of article views stems from social media referrals[1]. Platforms like Facebook and X (Twitter) have become the primary drivers for the dissemination of news, reshaping the way information flows through our digital society.

Traditionally, the propagation of news articles on social media was largely organic, driven by user engagement through likes, shares, and retweets. However, in recent times, news organizations have evolved their strategies to include the paid promotion of specific articles, harnessing the power of advertising to reach wider audiences [1]. The concept of promoting news articles on platforms like Facebook isn't inherently problematic, but it carries the potential for unintended consequences. For instance, it can inadvertently introduce biases into the information users encounter [2], or worse, become a means of manipulation [3]. The careful selection of news articles for promotion, combined with the micro-targeting capabilities offered by platforms like Facebook [4], can be exploited to advance various agendas, shaping public opinion and eliciting emotional responses from the audience. This approach often falls under the realm of propaganda, a method of persuasion frequently employed to further personal, political, or business agenda.

While advertisers from diverse backgrounds publish countless ads and boosted posts on Facebook daily, there is a key distinction in the content of the ads posted by news organizations. Most of news ads don't merely encourage users to subscribe or visit their homepage but explicitly promote individual news articles. The challenge lies in the fact that the titles (and snippets) of these ads carry message/information to the users encountering them. Unlike when users visit a news website, where they can exercise control over the articles they read, they have no such control over the sponsored news that populates their Facebook timeline. This lack of control leaves them vulnerable to the influence of the messaging, whether consciously or subconsciously.

Furthermore, a complex issue arises from Facebook's decision to exclude ads from news organizations from their 'social issues, elections, or politics' ad archive [2], even when these ads touch on political, electoral, or social issues. This omission negates the transparency requirements[3] imposed on other advertisers, placing news organizations in a unique position to publish paid political opinions without accountability. Consequently, there is a concerning potential for news organizations or third-party interest groups to meticulously select news articles that align with their agenda, all the while

[1] https://www.zdnet.com/article/social-media-is-key-driver-for-news-consumption/

[2] https://www.fb.com/business/help/issuesandpolitics; https://www.fb.com/business/help/313752069181919?id=288762101909005

[3] Including mandatory disclosure of amount spent to publish the ad, name of the entity/person responsible, etc. [5].

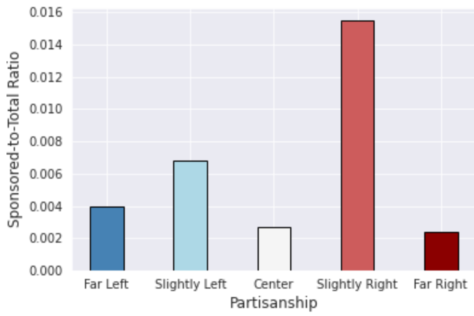


Fig. 1: Ratio of sponsored posts to all posts in each partisanship category.

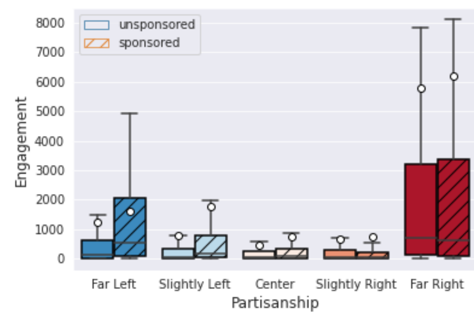


Fig. 2: Box plot of engagement. Black lines represent medians, and white dots represent means.

Partisanship	Sponsored (S)	Un-Sponsored (US)	Ratio (S/US)
Far Left	0.001925	0.00068	2.848
Slightly Left	0.002767	0.00062	4.498
Center	0.001090	0.00092	1.181
Slightly Right	0.001557	0.00088	1.768
Right	0.011814	0.00668	1.767

TABLE I: Normalized engagement across sponsored and unsponsored posts for different partisanship groups.

appearing legitimate because these ads direct users to well-known news outlets. When combined with the micro-targeting capabilities of sponsored post platforms [3], this becomes a potent tool for influencing users and spreading propaganda.

In this work, by gathering extensive longitudinal data from Facebook, we try to analyze the role of sponsored posts in spreading propaganda. Leveraging a reliable, state-of-the-art propaganda detection model, we demonstrate that sponsored posts indeed contain more propaganda compared to non-sponsored news posts on Facebook, worryingly bringing in higher engagement from the audience. We also check how this trend varies across the political spectrum. Additionally, we present a comprehensive analysis of propaganda spread by Facebook news pages around the time of the US Capitol attack (in January 2021), illustrating an escalation of propaganda during this period across both left-leaning and right-leaning media outlets.

With 2024 being touted as the biggest election year in history with more than half the world's population participating in polls[4], and the recent concerns regarding the potential misuse of large language models (LLMs) in spreading propaganda at scale [6], [7], we believe that our work will help raise awareness about the potential issues with sponsored news and the need to critically evaluate all the information users get on social media sites like Facebook.

II. Related Works

Propaganda on Social Media. The pervasiveness of social media platforms has created a fertile ground for proliferation of propaganda. Subsequently, several studies have aimed at analyzing and evaluating the impact of these platforms in influencing and reinforcing mass opinion across a variety of socially significant topics, including elections [9], [10], controversies [11], political-affiliations [12], and even ethnic violence [13]. Prior works have focused on propaganda dissemination on different social media platforms, such as Reddit [12], Twitter [14], and Facebook [15]–[17].

Detecting Propaganda. Propaganda is a subtle yet impactful way of influencing opinions that is hard to detect. As a consequence, considerable effort have been put into precisely defining propaganda and elaborating on nuanced propaganda techniques [8], [18]. The research community has proposed useful benchmark datasets [19]–[23], as well as developed effective propaganda detection methods, including BERT-based models [8], [12], [24], Large Language Models [25], among others. Additionally, various methods have been devised to tackle specific challenges in propagandistic content, including addressing code-switched social media text [26], employing multimodal approaches [27], and adapting strategies for multilingual propaganda [28], [29]. In this work, we utilize this line of work to select the best performing algorithm for detecting propaganda in news posts.

Interdisciplinary Efforts for Combating Propaganda. Concerns over online propaganda's reach have sparked broad research across disciplines. Psychologists and linguists have studied persuasion tacticssuch as emotional triggers and cognitive biases [30]–[34]. Sociologists have delved into the cultural and societal conditions that facilitate the influence of propaganda [31], [35], [36]. Legal scholars have advocated for regulating the use of technology towards responsible online spaces [37], [38]. Besides these efforts, various studies have focused on counteracting propaganda's impact through enhancing media literacy [39]. Our work complements these efforts by pointing out a novel source of propaganda and offers policy suggestions to tackle their spread.

III. Dataset Gathered

Following the data collection framework by [40], we gathered extensive longitudinal data comprising news posts and sponsored ads posted by media organizations on Facebook

[4]https://www.economist.com/interactive/the-world-ahead/2023/11/13/2024-is-the-biggest-election-year-in-history

Propaganda Type	Definition
Doubt	Questioning the credibility of someone or something.
Appeal to Fear/Prejudice	Attempt to increase opposition to a position by spreading fear/terror among the populace.
Exaggeration/Minimization	Attempting to make something seem either less or more significant than it truly is by employing exaggerations to diminish or amplify its importance.
Causal Oversimplification	Escaping the complexities of a situation by scapegoating a specific person or group, offering a superficial explanation that absolves others of responsibility.
Flag Waving	Emphasizing a profound sense of duty to intense national or group sentiment, such as race, gender, or political preference.
Loaded Language	Influencing a group by using emotionally charged (positive or negative) words and phrases
Name Calling or Labeling	Assigning derogatory labels or names to individuals or groups as a means of discrediting them or their ideas.
Slogans	Succinct and impactful phrases with an emotional appeal, utilizing labels and stereotypes.
Thought-terminating Cliché	Usage of phrases or words to stifle meaningful conversation and critical thought on a subject, offering simplistic answers or diverting attention from crucial ideas.
Repetition	Repeating a message with the expectation that the audience will eventually accept it.
Bandwagon	Showcasing a majority's support for a certain belief to persuade others.
Black and White Fallacy	Presenting two apparent solutions as the sole options, despite the existence of the only ones available when, in fact, there are more options.
Whataboutism	Instead of presenting solid evidence to challenge an opponent's argument, this approach seeks to weaken their perspective by alleging hypocrisy.
Obfuscation, Intentional Vagueness & Confusion	Employing vague generalizations to prompt the audience to draw their own conclusions.
Appeal to Authority	Depending on expert opinion without concrete evidence about the incident or event.
Red Herring	Introducing an irrelevant topic into the discussion shift individuals' focus.
Reductio ad Hitlerum	Proposing a conclusion solely based on the origin of something or someone, rather than considering its current meaning or context.
Straw Man	Substituting a comparable proposition for an opponent's, typically an extreme version, and refuting it instead of the original statement.

TABLE II: Eighteen fine-grained propaganda techniques proposed by [8].

over a period of 182 days, starting from 1st August 2020 till 30th January 2021. First, we utilized the Meta Ad Library[5] to collect active ads, i.e., the ads that were posted/run on Facebook during the data collection period, resulting in a total of 6,741,422 advertisements in the given time frame. Concurrently, we employed Meta's CrowdTangle API [41] to gather news posts from the Facebook pages of various news media organizations.

To identify these organizations, we took a two-pronged approach. First, we relied on an independent media watchdog 'Media Bias/Fact Check' which surveys news outlets and provides qualitative information about them, such as their political leaning and news quality [42]. Following this, we identified 2,863 Facebook pages corresponding to the media organizations covered by Media Bias/Fact Check. Subsequently, recognizing the rise of 'social media only' news channels that might elude traditional media watchdog groups [43], [44], we considered all Facebook pages which claimed to be 'News Media' in their 'About' section and posted at least one advertisement. In total, we compiled $10,492$ Facebook news channels, including details like their page_id, name, city, country, website, followers_count, creation time, misinformation status, and partisanship indications.

Overall, we collected 17,815,182 Facebook posts (on average, 97,885 posts per day) and 6,741,422 ads (37,040 ads per day). Even after we filter non-English posts[6] and Facebook pages with less than 10 posts, we end up with a collection of 12,506,833 posts which provides us with a rich and comprehensive dataset for the analysis.

Notably, the time period under examination holds particular significance for the study of social media news, as it spans the 2020 US Presidential Election, encompassing both pre-election and post-election posts shared by news outlets on Facebook. Particularly noteworthy inclusion is the time of the US Capitol attack (January 6, 2021) following the defeat of the former President Donald Trump. The dataset serves as a valuable resource for examining the combined impact of social media news, sponsorship, and the potential dissemination of propaganda within this context.

IV. Sponsored News Posts on Facebook

The dataset includes different types of ads (or sponsored posts) posted by various entities, including businesses, celebri-

[5]https://transparency.fb.com/en-gb/ researchtools/ad-library-tools/

[6]We keep only English posts as our propaganda classifier (explained in later section) was trained on English data alone.

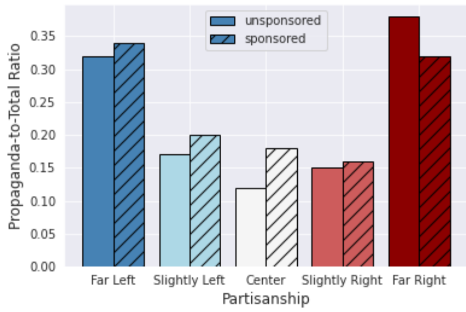


Fig. 3: Ratio of propaganda posts to total posts by sponsorship and partisanship.

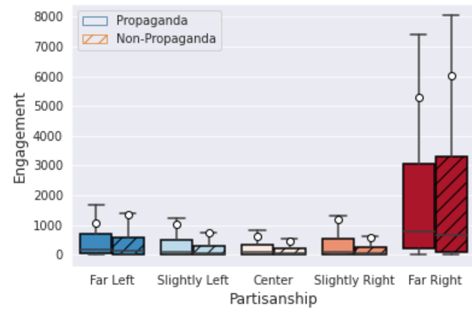


Fig. 4: Engagement of propagandistic and non-propagandistic across various partisanships.

ties, political parties, and news media outlets. We first identified the sponsored news posts within this dataset by comparing the destination URL of each advertisement with the destination URL of the collected news posts. A match between the two URLs indicates a sponsored post. While this methodology may not capture all sponsored posts, it ensures the accuracy of identified sponsored content. Overall, we found 72,113 sponsored posts (out of the total 12,506,833 posts) using this approach. For a comprehensive analysis, we categorize the identified sponsored posts into various partisanship groups. To this end, we employ the partisanship classifications from Media Bias/Fact Check [42], focusing on $2,863$ Facebook pages they cover, categorized as far *left*, *slightly left*, *center*, *slightly right*, and *far right*. Next, we examine how various media outlets leverage Facebook ads to expand their reach.

Sponsored-to-Total-Post ratio across political spectrum. Figure 1 reveals the relative prevalence of sponsored content across partisanship categories, expressed as the ratio of sponsored posts to total posts. Our findings indicate a notable trend: news channels affiliated with either the far left, slightly left, or slightly right political leanings tend to exhibit higher sponsored-to-total post ratios compared to the center. This suggests a potential association between political orientation and susceptibility to sponsorship, with some leaning groups attracting more commercial partnerships than others. However, it is important to note that this trend does not appear to extend to the far-right channels, which deviate from the pattern by displaying a lower sponsorship ratio. We also observed that newly established Facebook pages with a political inclination tend to exhibit a higher ratio of sponsored to total posts, indicating a potential strategy to quickly and effectively disseminate information and increase reach.

Analyzing engagement with sponsored posts. We analyze the engagement of sponsored and unsponsored posts, by measuring engagement as the sum of the corresponding likes, reactions, and comments. As depicted by Figure 2, across all partisanship categories (with a negligible exception favoring unsponsored posts in *slightly-right* leaning pages), sponsored posts demonstrate higher reach compared to unsponsored posts of the same partisanship. The engagement of sponsored posts in left and right-leaning categories surpasses that of center-oriented pages.

Table I presents the engagement levels for each partisanship category, normalized by the follower count of the corresponding Facebook page, for both sponsored and non-sponsored posts. While there is only a slight increase in engagement for the sponsored posts of center-leaning pages, there is a notable increase in the corresponding engagement for right- and left-leaning pages, which suggests a deliberate approach in the design of sponsored posts to encourage higher user engagement. Hence, based on the above analysis, it is clear that sponsored posts on Facebook is an effective strategy for gaining higher user engagement as compared to unsponsored posts.

V. Propaganda Detection

Next, we focus on identifying propaganda posts on Facebook. Propaganda detection has typically been posed as a multi-class classification problem [8], [12], [25], where the classification labels differ based on the dataset under consideration. For our analysis, we utilize the multi-granularity propaganda detection model (MGN-ReLU) proposed by [8]. This model has been trained on a large, high-quality benchmark dataset that features both sentence-level and span-level annotations, i.e., each sentence is manually annotated at the sentence level as either *propaganda* or *non-propaganda*, and each text span within the sentence belonging to any of the 18 propaganda classes (described in Table II) is annotated with the corresponding propaganda technique. We call this dataset as the QCRI dataset[7]. As shown by [8], due to the extra supervision provided by the span-level annotations, fine-grained classification enhances the model's performance at the sentence level. Consequently, the model not only provides binary classification on input sentences but also offers insights into the involved propaganda techniques. This also improves the model's explainability, thereby enhancing its overall reliability. The reliability of this model is corroborated by subsequent studies such as [12], which show that the model is robust to topical biases in the annotated dataset and learns

[7]Since it was contributed by researchers from the Qatar Computing Research Institute (QCRI) [8].

Model	Recall	Precision	F1-score
Random	0.501	0.245	0.329
BERT	0.556	0.557	0.556
ALBERT	0.560	0.527	0.543
XLNet	**0.601**	0.518	0.556
T5	0.4535	**0.607**	0.519
MGN-ReLU	0.593	0.554	**0.577**

TABLE III: Comparison of classifiers on the QCRI test for sentence-level classification. Best results highlighted in bold.

linguistic patterns in the dataset rather than being influenced by topical confounds, which is desirable.

For establishing the suitability of the MGN-ReLU model for our analysis, we perform a comparison against several prominent classification models. We fine-tune a suite of well-known transformer-based classifiers such as BERT [45], ALBERT [46], XLNet [47], and T5 [48] on the sentence-level QCRI dataset using the hyperparameters described in [8]. As an additional baseline, we also report the performance of a Random classifier that classifies each sentence uniformly at random. Note that we do not fine-tune the MGN-ReLU model; rather we utilize the MGN-ReLU model provided by [8], which is already trained on the QCRI dataset. Table III shows the performance of the models for the binary, sentence-level classification on the QCRI dataset. As expected, all models perform significantly better compared to Random classification. Notably, the MGN-ReLU model emerges as the best classifier, achieving the best F1-score, and reasonably good Precision and Recall scores. Recently, large language models (LLMs) have also been employed for propaganda detection. However, they were found to perform worse than BERT-based models on the QCRI dataset [25]. Hence, we proceed with the MGN-ReLU classifier in this work.

To further validate the MGN-ReLU classifier's reliability on our dataset, we randomly sampled 100 posts and manually annotated them. Subsequently, we evaluated the classifier's performance on this subset of data. Remarkably, the classifier exhibited strong performance, achieving precision, recall, and F1-score values of 0.76, 0.59, and 0.67, respectively. Notably, this performance exceeded that observed on the QCRI test set, providing compelling evidence supporting the confident utilization of this classifier for our dataset analysis.

VI. Propaganda in Facebook Posts

In this section, we conduct a thorough analysis of the posts in our dataset, considering the classification labels (*propaganda* or *non-propaganda*) assigned through the process described in the previous section. Our investigation includes a comprehensive study of *sponsorship*, *partisanship* (Far Left, Slightly Left, Center, Slightly Right, and Far Right), and *engagement* (reactions, comments, etc.) across both propaganda and non-propaganda labels. Note that the fine-grained classification of posts in our dataset follows the same approach as that used for the news articles in the QCRI dataset [8]. However, an entire Facebook post, typically comprising a few sentences, is classified as a *propaganda* post only if it contains at least one sentence predicted to be propagandistic by the classifier.

Q. Do sponsored posts spread more propaganda? We find that approximately 19% of sponsored posts are classified as propaganda, compared to around 16% of unsponsored posts. This suggests that sponsored posts are more likely to contain propaganda. To statistically validate this observation, while considering the substantial difference in the total number of unsponsored (around 12.4 million) and sponsored (near 72K) posts, we performed a Chi-square test.The test reveals a significantly higher proportion of propagandistic posts among sponsored posts compared to unsponsored posts, with a χ^2 value of 264.29 and $p << 0.05$. Next, when we examine the distribution of propaganda posts across various partisan affiliations in both sponsored and unsponsored posts, we observe in Figure 3 that the overall partisanship distribution remains quite similar. However, there's a noticeable bias towards Far Left and Far Right leanings. Notably, almost 70% of the propaganda posts originate from news channels with Far Left and Far Right political leanings, regardless of the type of sponsorship. This correlation strongly suggests that the political bias of these channels is positively associated with their use of propaganda.

We also analyzed various propaganda techniques present in the posts. Table IV displays the top 5 propaganda techniques found in our dataset. This table provides insights into the distribution of posts associated with each technique across different partisan affiliations and sponsorship categories. A noteworthy observation is the general trend of sponsored posts exhibiting a relatively higher prevalence of propaganda compared to unsponsored posts across all partisanships. The most significant disparity in terms of sponsorship is particularly evident in the case of Far Right-leaning propaganda posts, with sponsored posts being up to twice as propagandistic in terms of numbers.

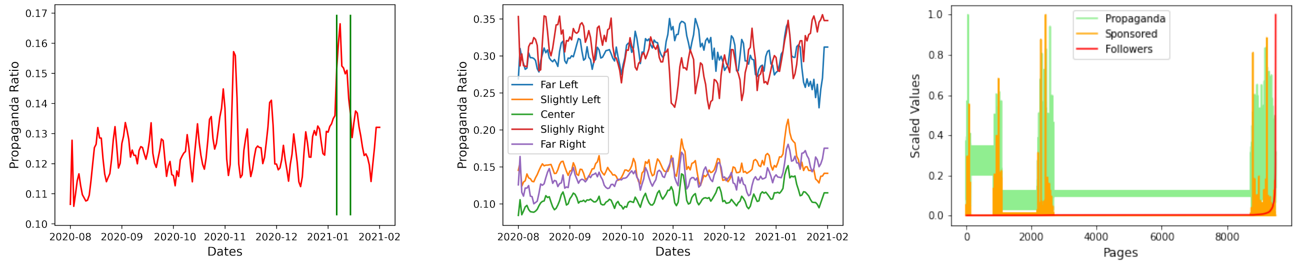
Q. Do propagandistic posts generate more engagement? Recall that, in the previous sections, we've already established that sponsored posts lead to more engagement and that sponsored content is more likely to contain propaganda. Here, we examine the engagement levels of propaganda and non-propaganda posts (across various partisanship categories). To gauge engagement, we utilize the total sum of reactions and comments on a post, normalized by the number of followers of the corresponding channel. Figure 4 illustrates the engagement of propaganda posts categorized by their partisanship. Regardless of the partisanship, propaganda posts consistently exhibit higher engagement compared to non-propaganda posts (with a minor exception in the 'Far Right' partisanship group).

Q. Do influential Facebook pages tend to post more propaganda? Now we study whether highly influential Facebook pages, indicated by a substantial follower count[8] tend to share more propagandistic content. Figure 5c shows the distribution

[8]We observed a high correlation between the 'engagement' and 'followers count' of a page, hence, using 'engagement' as a measure of a page's influence gives qualitatively similar results.

Propaganda Type	Overall (S)	Overall (US)	Far Left (S)	Far Left(US)	Slight Left (S)	Slight Left (US)	Center (S)	Center (US)	Slight Right (S)	Slight Right (US)	Far Right (S)	Far Right(US)
Loaded Language	***0.14***	0.12	*0.24*	0.24	***0.15***	0.13	***0.13***	0.08	***0.12***	0.11	***0.25***	0.18
Name Calling/Labelling	***0.07***	0.06	*0.14*	0.14	*0.06*	0.06	***0.06***	0.04	***0.06***	0.05	***0.16***	0.1
Flag Waving	***0.03***	0.02	***0.06***	0.04	***0.03***	0.02	***0.03***	0.01	0.02	***0.02***	***0.08***	0.04
Exaggeration/Minimisation	*0.02*	0.02	***0.05***	0.03	***0.03***	0.02	***0.02***	0.01	0.02	0.02	***0.04***	0.02
Doubt	*0.02*	0.02	***0.06***	0.05	***0.03***	0.02	***0.02***	0.01	*0.02*	0.02	*0.07*	**0.18**

TABLE IV: Fractions of Top-5 propaganda types spread across sponsorship and partisanship. (S) and (US) stand for sponsored posts and unsponsored posts respectively.



(a) (b) (c)

Fig. 5: (a) Ratio of propaganda posts to total posts over time by all Facebook channels. (b) Plot of ratio of propaganda posts to total posts over time by US-based Facebook channels alone. (c) Line plot showing the distribution of the fraction of propaganda and sponsored posts for Facebook pages sorted by their followers' count.

of the fraction of propaganda as well as sponsored posts posted by Facebook pages within our dataset, arranged in a non-decreasing order of their followers' count[9]. Although a clear linear or monotonic correlation is not evident between a page's follower count[10] and its frequency of posting sponsored or propagandistic content, it can be seen that propaganda is more prevalent on pages with either very low or very high follower counts (as depicted by the co-occurring spikes of propagandistic and sponsored contents for such pages). Specifically, the bottom 25% and top 25% pages by follower count post significantly higher ($p < 0.05$ in Mann-Whitney U Test [49]) propaganda content compared to the overall distribution. Delving deeper, we also find that any page with $> 20\%$ sponsored posts tends to spread about 2.31 times more propaganda compared to pages posting $< 20\%$ sponsored content.

VII. Case Study: 2020 US Presidential Election

While so far we have reported the analyses of propaganda at a longer timescale, we now delve into a particular event. Our data collection period encompasses significant events like the US Presidential Election on November 3rd, 2020, and the subsequent US Capitol attack in Washington, D.C. on January 6th, 2021. Our investigation entails a comprehensive scrutiny of propaganda disseminated through news pages on Facebook, spanning the periods preceding the election, the election itself, and the aftermath. This analysis seeks to offer insights into the role and importance of propaganda in the political landscape during this pivotal period.

A. Pre-Election and Election Period

The influence of social media on political opinions is substantial, often contributing to polarization by recommending content aligning with users' existing views. Particularly on Facebook, where news channel pages boast large followings, there is a tendency to disseminate propagandistic content that can sway the opinions of their followers. Table V presents detailed examples of propaganda dissemination by both left-wing and right-wing news channels during the pre-election period.

Examining Figure 5a, which tracks the propaganda trends from news pages over six months corresponding to our dataset's timeline, reveals a noteworthy pattern. The graph illustrates the proportion of propaganda posts relative to total posts. A noticeable peak emerges during the first week of November, falling between the two most statistically significant changepoints[11], aligning with the election date (November 3, 2020). This surge in propaganda posts seems to be initiated around mid-September, reaches its zenith in early November, and undergoes subsequent decline in December. This observation strongly suggests that the news pages on social media exhibit a preference for employing propaganda as a subtle tool to influence their audience, particularly during pivotal events like elections.

B. Post Elections: Capitol Attack

The aftermath of the 2020 US presidential elections witnessed the alarming events of the Capitol attack, where around 2000 individuals, seemingly fueled by the then president's speech, marched to the Capitol to protest alleged voting

[9] For consistency, all values shown in the figure have been scaled between 0 and 1 using min-max scaling.

[10] Low Pearson (0.096) and Spearman (0.383) correlation coefficients.

[11] We performed the changepoint analysis using the `Dynp` algorithm[12].

Channel	Partisanship	Post Content	Propaganda Type
The New Civil Rights Movement (Followers: 377679)	Left	"**Do all of Putin's operatives spread disinfo that can so easily be fact checked?**"[*] Richard Grenell, President Donald Trump's former Acting Director of National Intelligence, is under fire after posting a 2019 photo of Joe Biden and attacking him as **phony**[**] for not wearing a mask. Since the photo was clearly taken months before the coronavirus was even discovered, Grenell is ... 'Disinformation **Grifter**[***]': Ex-Trump Intel Chief's Anti-Biden Stunt Backfires, Earns Him a 'Manipulated Media' Label	Doubt[*], Loaded Language[**], Name-Calling[***]
The Stranger (Followers: 128486)		—Election week 2020 begins tonight —Biden sweeps Dixville Notch —When will we know if we're still living in a democracy?After four long years that felt like a thousand **endless nightmares**[*]: Election week 2020 is finally here. East coast polls (plus Georgia and Indiana) close at 4 p.m. PST, and we'll start seeing some results about a half-hour or an hour afterwards. Slog goes live shortly thereafter. Stay tuned for upda... Slog AM: Alright **You Nervous Little Freaks**[**], It's Time to Boot the **Bad President**[**] and End **This American Carnage**[***]	Exaggeration[*], Name calling[**], Flag waving[***]
Pamela Geller (Followers: 1291098)	Right	It's **one bombshell after**[*] another now. BOMBSHELL AUDIO! Hunter Biden Confesses Partnership With **"The F**king Spy Chief of China"**[**] … Joe Biden Named In Criminal Case Witness - Geller Report News	Loaded Language[*], Name calling[**]
PJ Media (Followers: 405847)		"This will get ugly." In the Battle for Florida, It Looks Like Democrats are Heading for a **Bloodbath**[*]	Loaded Language[*]

TABLE V: Facebook posts before the US Elections from the Left and Right classified news channels, these posts clearly indicate the type of propaganda being spread out through the news channels on Facebook.

Channel	Post Content	Propaganda Type
100 Percent Fed up	**This isn't about Democrats or Republicans; this is about America**[*]. American Patriots are 100 Percent Fed Up with the corruption! Now arrives the hour of action! We've got to do this now! 100 Percent Fed Up – The Biden Campaign's primary defense is don't hear the evidence. That is why the pu... The Gateway Pundit: **WOW! Stop The Steal!**[**] Arrives…The Hour Of Action	Flag waving[*], Slogan[**]
The Globe and Mail (Followers: 786k)	Vice President Pence Can Stop the Steal and Keep the Peace"All that is necessary for the triumph of evil is that good men do nothing." (Edmund Burke) I suspect Vice President Mike Pence has quoted that many times. January 6 might be his opportunity to live out his day to **be the good man who stopped evil**[*]. About **half of our nation**[**] understands that Trump's ...Vice President Pence Can Stop The Steal And Keep The Peace	Name calling[*], Flag waving[**]

TABLE VI: Facebook posts after the US elections and before the Capitol Attack.

fraud[13]We analyze the influence of social media on this incident to understand and emphasize the extent of propaganda spread and its possible ramifications. In table VI, we present manually labeled examples of propaganda dissemination by Facebook channels during the post-election and pre-attack period. During this phase, we observed a surge in propaganda employing techniques like "slogan", "name-calling", and "flag-waving". These tactics aimed at provoking individuals to take action against the election results without presenting substantiated arguments. Concurrently, various Facebook campaigns emerged, encouraging people to protest by promoting "slogan" and "flag-waving" propaganda. A notable example is the relentless promotion of the slogan "Stop the Steal!" to such an extent that Facebook intervened to mitigate posts containing this slogan[14]

Revisiting Fig. 5a, the correlation between the Facebook propaganda dissemination and the timing of the Capitol attack is quite evident. The highest peak in propaganda around the second week of January precisely aligns with the date of the Capitol attack (7th January 2020). Figure 5b further elucidates the dynamic response to the surge in propaganda. Particularly we see an increase in right-wing propaganda following the period of the Capitol attack in order to pacify the protest, while the left-wing propaganda declines. Interestingly, we also witness a peak in propaganda across all partisan groups during the period surrounding the attack, specifically in the first and second weeks of January, 2020. This suggests a link between the surge in propaganda on social media and real-world events like the attack, emphasizing the influential role that online propaganda on social media can play in shaping offline actions and consequences.

[13]https://www.usatoday.com/in-depth/news/2021/02/01/ civil-war-during-trumps-pre-riot-speech-parler-talk-grew-darker/ 4297165001/

[14]https://www.nytimes.com/2021/01/11/us/facebook-stop-the-steal.html

VIII. Conclusion

In this work, we emphasized the influence of sponsored news posts on propaganda dissemination on Facebook. Through extensive analysis and experiments on a curated dataset of Facebook posts, using advanced propaganda detection methods, we found that sponsored news posts are more likely to be propagandistic and elicit increased user engagement. Additionally, we conducted a detailed analysis of Facebook posts surrounding the 2021 US Capitol Attack, revealing patterns in propaganda dissemination by various news channels during that time.

Limitations. We acknowledge that although we have made extensive efforts to justify our hypotheses, our analysis is constrained by the labels assigned through an imperfect propaganda classifier. Additionally, despite the comprehensive scope of the dataset, which spans a significant timeframe, the dynamic nature of the socio-political landscape introduces a potential limitation in its temporal generalizability.

Reproducibility. We aim to release our dataset and codebase after acceptance.

References

[1] K. A. Johnson and B. St. John III, "News stories on the facebook platform: Millennials' perceived credibility of online news sponsored by news and non-news companies," *Journalism Practice*, 2020.

[2] A. Chakraborty, S. Ghosh, N. Ganguly, and K. P. Gummadi, "Dissemination biases of social media channels: On the topical coverage of socially shared news," in *ICSWM*, 2016.

[3] F. N. Ribeiro, K. Saha, M. Babaei, L. Henrique, J. Messias, F. Benevenuto, O. Goga, K. P. Gummadi, and E. M. Redmiles, "On microtargeting socially divisive ads: A case study of russia-linked ad campaigns on facebook," in *FAccT*, 2019.

[4] G. Venkatadri, A. Andreou, Y. Liu, A. Mislove, K. P. Gummadi, P. Loiseau, and O. Goga, "Privacy risks with facebook's pii-based targeting: Auditing a data broker's advertising interface," in *2018 IEEE Symposium on Security and Privacy (SP)*. IEEE.

[5] Meta, "Increasing our ads transparency," https://about.fb.com/news/2023/02/increasing-our-ads-transparency/, February 2023.

[6] J. A. Goldstein, G. Sastry, M. Musser, R. DiResta, M. Gentzel, and K. Sedova, "Generative language models and automated influence operations: Emerging threats and potential mitigations," 2023.

[7] C. Chen and K. Shu, "Combating misinformation in the age of llms: Opportunities and challenges," 2023.

[8] G. Da San Martino, S. Yu, A. Barrón-Cedeño, R. Petrov, and P. Nakov, "Fine-grained analysis of propaganda in news articles," in *EMNLP-IJCNLP*, 2019.

[9] M.-A. Rizoiu, T. Graham, R. Zhang, Y. Zhang, R. Ackland, and L. Xie, "Debatenight: The role and influence of socialbots on twitter during the 1st 2016 u.s. presidential debate," 2018.

[10] D. Chernobrov and E. Briant, "Competing propagandas: How the united states and russia represent mutual propaganda activities," *Politics*, 2022.

[11] A. Guimaraes, O. Balalau, E. Terolli, and G. Weikum, "Analyzing the traits and anomalies of political discussions on reddit," *ICWSM*, 2019.

[12] O. Balalau and R. Horincar, "From the stage to the audience: Propaganda on Reddit," in *EACL*. ACL, 2021. [Online]. Available: https://aclanthology.org/2021.eacl-main.309

[13] P. Mozur, "A genocide incited on facebook, with posts from myanmar's military," 2018. [Online]. Available: https://www.nytimes.com/2018/10/15/technology/myanmar-facebook-genocide.html

[14] S. Guarino, N. Trino, A. Celestini, A. Chessa, and G. Riotta, "Characterizing networks of propaganda on twitter: a case study," *Applied Network Science*, 2020.

[15] H. Seo and H. Ebrahim, "Visual propaganda on facebook: A comparative analysis of syrian conflicts," *Media, War & Conflict*, vol. 9, no. 3, pp. 227–251, 2016.

[16] P. L. Moravec, A. Collis, and N. Wolczynski, "Countering state-controlled media propaganda through labeling: Evidence from facebook," *Information Systems Research*.

[17] F. Pierri, L. Luceri, N. Jindal, and E. Ferrara, "Propaganda and misinformation on facebook and twitter during the russian invasion of ukraine," ser. WebSci '23. ACM, 2023.

[18] C. R. Miller, "The techniques of propaganda. from "how to detect and analyze propaganda"," 1939.

[19] Z. Kmetty, V. Vincze, D. Demszky, O. Ring, B. Nagy, and M. K. Szabo, "Partelet: A hungarian corpus of propaganda texts from the hungarian socialist era," in *LREC'20*. Marseille, France: European Language Resources Association, 2020. [Online]. Available: https://aclanthology.org/2020.lrec-1.290

[20] V. Baisa, O. Herman, and A. Horak, "Benchmark dataset for propaganda detection in czech newspaper texts," in *RANLP'19*. INCOMA Ltd., 2019. [Online]. Available: https://aclanthology.org/R19-1010

[21] G. Da San Martino, A. Barrón-Cedeño, H. Wachsmuth, R. Petrov, and P. Nakov, "SemEval-2020 task 11: Detection of propaganda techniques in news articles," in *SemEval-2020*. ICCL, 2020.

[22] J. Tian, M. Gui, C. Li, M. Yan, and W. Xiao, "MinD at SemEval-2021 task 6: Propaganda detection using transfer learning and multimodal fusion," in *SemEval-2021*. ACL, 2021. [Online]. Available: https://aclanthology.org/2021.semeval-1.150

[23] K.-H. Huang, K. McKeown, P. Nakov, Y. Choi, and H. Ji, "Faking fake news for real fake news detection: Propaganda-loaded training data generation," in *ACL*, 2023.

[24] M. Abdullah, O. Altiti, and R. Obiedat, "Detecting propaganda techniques in english news articles using pre-trained transformers," in *ICICS'22*, 2022.

[25] K. Sprenkamp, D. G. Jones, and L. Zavolokina, "Large language models for propaganda detection," 2023.

[26] M. U. Salman, A. Hanif, S. Shehata, and P. Nakov, "Detecting propaganda techniques in code-switched social media text," 2023.

[27] V. Ng and S. Li, "Multimodal propaganda processing," *AAAI*, 2023.

[28] V. Solopova, O.-I. Popescu, C. Benzmüller, and T. Landgraf, "Automated multilingual detection of pro-kremlin propaganda in newspapers and telegram posts," 2023.

[29] A. Purificato and R. Navigli, "APatt at SemEval-2023 task 3: The sapienza NLP system for ensemble-based multilingual propaganda detection," in *SemEval-2023*, A. K. Ojha, A. S. Doğruöz, G. Da San Martino, H. Tayyar Madabushi, R. Kumar, and E. Sartori, Eds. ACL.

[30] W. Cai, "Analysis of the promotion of consumer psychological analysis and marketing to sports propaganda," *Revista de Psicología del Deporte (Journal of Sport Psychology)*, 2023.

[31] K. Young, F. B. Lindstrom, and R. A. Hardert, "Kimball young on social psychology, rural sociology, and anthropology at wisconsin, 1926-1940," *Sociological Perspectives*, 1989. [Online]. Available: http://www.jstor.org/stable/1389124

[32] A. Barfar, "A linguistic/game-theoretic approach to detection/explanation of propaganda," *Expert Systems with Applications*, 2022.

[33] J. Zienkowski, "Propaganda and/or ideology in critical discourse studies," *DiscourseNet Collaborative Working Paper Series*, 2021.

[34] R. Torok, "Symbiotic radicalisation strategies: Propaganda tools and neuro linguistic programming," 2015.

[35] D. D. Chaudhari and A. V. Pawar, "Propaganda analysis in social media: A bibliometric review," *Information Discovery and Delivery*, 2021.

[36] M. Malhan and P. P. Dewani, "Propaganda as communication strategy: Historic and contemporary perspective," *Academy of Marketing Studies Journal*, 2020.

[37] C. M. Corbin, "The unconstitutionality of government propaganda," *Ohio St. LJ*, 2020.

[38] Halina Swieboda, Mateusz Kuczabski, Ryszard Szpyra, Tomasz Zawadzki, Tomasz Walecki, and Pawel Stobiecki, "Social control in the face of digital propaganda," *European Research Studies Journal*, 2021.

[39] C. of Europe, "Dealing with propaganda, misinformation and fake news," 2023. [Online]. Available: https://www.coe.int/en/web/campaign-free-to-speak-safe-to-learn/dealing-with-propaganda-misinformation-and-fake-news

[40] L. Edelson, M.-K. Nguyen, I. Goldstein, O. Goga, D. McCoy, and T. Lauinger, "Understanding engagement with u.s. (mis)information news sources on facebook," ser. IMC '21. New York, NY, USA: ACM, 2021. [Online]. Available: https://doi.org/10.1145/3487552.3487859

[41] Tess, "Crowdtangle api," https://help.crowdtangle.com/en/articles/1189612-crowdtangle-api, 2024.

[42] Dave Van Zandt, "Media biasfact checkk - search and learn the bias of news media," https://mediabiasfactcheck.com, 2024.

[43] P. Bengani, "Hundreds of 'pink slime' local news outlets are distributing algorithmic stories and conservative talking points," *Columbia Journalism Review*, 2019.

[44] F. Ribeiro, L. Henrique, F. Benevenuto, A. Chakraborty, J. Kulshrestha, M. Babaei, and K. Gummadi, "Media bias monitor: Quantifying biases of social media news outlets at large-scale," in *ICWSM*, 2018.

[45] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.

[46] Z. Lan, M. Chen, S. Goodman, K. Gimpel, P. Sharma, and R. Soricut, "Albert: A lite bert for self-supervised learning of language representations," *arXiv preprint arXiv:1909.11942*, 2019.

[47] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," in *NeurIPS*, H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, Eds. Curran Associates, Inc. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2019/file/dc6a7e655d7e5840e66733e9ee67cc69-Paper.pdf

[48] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu, "Exploring the limits of transfer learning with a unified text-to-text transformer," 2023.

[49] P. E. McKnight and J. Najab, *Mann-Whitney U Test*. John Wiley & Sons, Ltd, 2010. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470479216.corpsy0524