How the global war on terror killed the prospect of justice for Kenyan victims of violence
Analysing Strategic Communications through early modern theatre
Strategic Communications as a tool for great power politics in Venezuela
The beginning of warfare on the internet: Zapatista Strategic Communications
Measuring the effect of Russian Internet Research Agency information operations in online conversations
Reverse engineering Russian Internet Research Agency tactics through network analysis
From swords to ploughshares: time for a CVE step-change?
On finding the ethical in the age of digital battle spaces
MEASURING THE EFFECT OF RUSSIAN INTERNET RESEARCH AGENCY INFORMATION OPERATIONS IN ONLINE CONVERSATIONS

John D. Gallacher and Marc W. Heerdink

Abstract

The Internet has given new opportunities to those who wish to interfere and disrupt society through the systematic manipulation of social media. One goal of these cyber-enabled information operations is to increase polarisation in Western societies by stoking both sides of controversial debates. Whether these operations are successful remains unclear. This paper describes how novel applications of computational techniques can be used to test the impact of historical activity from the Russian Internet Research Agency (IRA) on two social media platforms: Twitter and Reddit. We show that activity originating from the Russian IRA had a measurable effect on the subsequent conversations of genuine users. On Twitter, increases in Russian IRA activity predicted subsequent increases in the degree of polarisation of the conversation surrounding the Black Lives Matter movement. On Reddit, comment threads started by Russian IRA accounts contained more toxic language and identity-based attacks. We use causal analysis modelling to further show that Russian IRA activity in existing threads caused measurable changes in the conversational quality of the following 25-100 posts. By developing methods to measure the impact of information operations in online conversations and demonstrating a measurable effect on genuine conversations, our study provides an important step in developing effective countermeasures.
Keywords—information operations, social media, social psychology, group polarisation, disinformation, strategic communications

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Introduction

The rapid development of the Internet has enabled people everywhere to connect, communicate, and distribute information globally at an unprecedented scale. However, some use this opportunity for connection to divide rather than to bring people together. In recent years, a great deal of attention has been focused on groups that conduct deliberate social media activities to divide and polarise societies. These activities include the use of artificial social media accounts, paid advertisements, and automated scripts designed to spread disinformation. These activities are constituents of wider information operations campaigns that seek to gain a competitive international advantage over traditional adversaries. While the approach itself is not new—similar methods targeting the psychology of civilian populations can be traced back to the Roman, Persian, and Chinese empires—these methods have transformed in the digital age and now increasingly rely on social media platforms that provide global reach and can target individuals directly for a fraction of the cost of traditional methods. This phenomenon is characterised by sustained and pervasive efforts, which

3 Jen Weedon, William Nuland, and Alex Stamos, Information Operations and Facebook, Facebook, 2017.
peak around election cycles, although elections are not the sole focus. This persistent engagement, short of traditional thresholds for conflict, makes it difficult to construct robust responses.6

In 2014, the World Economic Forum identified the rapid spread of misinformation online as one of the top 10 threats to society.7 Since this warning, the deliberate spread of misleading information has been linked to political earthquakes such as the 2016 US Election8, the 2016 UK Brexit referendum9, and the rise of populist parties across Europe10, as well as to political violence in Brazil11, Myanmar12, and India13. All these events are connected by one consistent trend—an increase in social polarisation, defined as the process of increased segregation into distinct social groups, separated along racial, economic, political, religious or other lines.14 Hostile information operations on social media show no evidence of slowing down15, while social media platforms stand accused of failing to act decisively in combating this threat16. Understanding the consequences of these activities is essential to developing effective defences. In-depth knowledge about the consequences of these hostile narratives should inform policy decisions aimed at countering them, yet very little is known about the effect these activities have on the online conversations of genuine citizens, and whether or not they achieve their goals.

In this study we developed methods to address this question and to measure the effect of artificial social media manipulation on subsequent human conversations, using publicly attributed information operations from the Russian state as a case study. Recently, evidence shows that the Russian government has been engaged in a substantial effort to sway public opinion on a number of

key topics, at home and abroad, through a prolonged information campaign.\textsuperscript{17} This campaign includes disinformation, artificial social media accounts imitating a grass-roots movement, paid advertisements, and automated scripts designed to hijack filtering algorithms in order to disseminate content to the widest possible audience.\textsuperscript{18} These accounts also promoted real-world protests and demonstrations, often encouraging both sides of controversial topics. While the 2016 US presidential election seems to have been one important focus for these activities, the wider intention appears to have been to polarise online conversations and sow social division along social as well as political lines.\textsuperscript{19}

\textit{The relationship between disinformation and polarisation}

People increasingly use social media as their primary source for news and information, with two-thirds of Americans and half of adults in the developing world getting their news from social media platforms.\textsuperscript{20} Ideological alignment with specific groups and ideas is often more obvious in online environments than it is offline,\textsuperscript{21} either due to structural features, such as profile pictures or group memberships, or because of the content shared by users. For this reason, separation into groups of likeminded people is more likely to occur online than offline. This facilitates group polarisation, a social-identity-based phenomenon where individuals endorse more extreme ideological positions following a discussion with other in-group members.\textsuperscript{22} This increased polarisation may encourage group members to take a more extreme position on certain issues, or may result in an increased dislike of members of other groups without a change in their position on that issue.\textsuperscript{23}

\begin{thebibliography}{99}
\bibitem{17} Weedon et al., \textit{Information Operations and Facebook}; Intelligence Community Assessment, \textit{‘Assessing Russian Activities’}.
\bibitem{19} Sebastian Bay et al., \textit{Responding to Cognitive Security Challenges}, (Riga, Latvia: NATO StratCom CoE, 2019); DiResta et al., \textit{‘Tactics & Tropes’}.
\end{thebibliography}
Messages emphasising inter-party conflict have been shown to reinforce social polarisation and are easy to distribute in online environments. Messages containing strong partisan cues that match an individual’s beliefs can encourage them to accept and share inaccurate information,\textsuperscript{24} while messages that agree with pre-held stereotypes can facilitate an individual’s acceptance of inaccurate information about an out-group.\textsuperscript{25} Equally, polarised conversations can lead to increased dissemination of disinformation. People are more likely to trust inaccurate information if it elicits anger and aligns with their existing opinions.\textsuperscript{26} Content that is highly controversial or elicits greater moral outrage is more likely to be shared by social media users,\textsuperscript{27} while erroneous content can be made more sensational than true content and therefore more likely to inspire fear and disgust, which in turn encourages sharing the content faster and farther.\textsuperscript{28} Online environments may create ‘echo chambers’—networks of like-minded people who confirm each other’s opinions instead of promoting critical thinking\textsuperscript{29}—exacerbating these effects. Disinformation spreads more quickly within these closely connected groups due to a lack of dissenting voices.\textsuperscript{30} This may facilitate the creation of a society that is increasingly polarised and misinformed\textsuperscript{31} as people are more likely to be affected by inaccurate information if they see it more frequently, especially in cases where fresh exposure influences decision-making.\textsuperscript{32}

\textsuperscript{29} Cass R. Sunstein, \#Republic: Divided Democracy in the Age of Social Media (Princeton University Press, 2017).
Recent evidence suggests that echo-chambers may not be forming as often as first expected\(^{33}\), and users are, in fact, exposed to more cross-cutting information online than they would select purely based on choice.\(^{34}\) Even so, this cross-cutting information may not have a positive effect. Users with more extreme ideological positions are more active on social media\(^{35}\) and exposure to opposing views online can also increase polarisation by highlighting areas of disagreement.\(^{36}\) Both situations provide opportunities for those who wish to leverage the polarising effects of social media, either through infiltrating echo chambers to spread negative messages about an out-group without opposition, or by engaging with someone while posing as an out-group member in order to antagonise and create a negative impression of the out-group as a whole.

**The St. Petersburg Troll Farm and Online Polarisation**

From as early as 2012, information operations conducted over social media have been targeting citizens in the West.\(^{37}\) These operations originate from the St Petersburg ‘troll farm’ run by the Russian Internet Research Agency (Russian IRA). The agency aims to influence online conversations about regional, national, and international issues that affect Russian foreign and domestic policy interests.\(^{38}\) Online manipulation can take the form of ‘trolling’ orchestrated from human-controlled accounts or political communications spread—by automated accounts (bots).\(^{39}\) Since 2012, these campaigns have grown steadily in number and scale,\(^{40}\) and have gained much international attention, particularly surrounding the 2016 US presidential election.\(^{41}\)

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37 Howard et al., ‘The IRA, Social Media and Political Polarization’.


40 Howard et al., ‘The IRA, Social Media and Political Polarization’; DiResta et al., ‘Tactics & Tropes’.

41 Intelligence Community Assesment, ‘Assessing Russian Activities’.
Over the course of 2018, large, open-source datasets detailing posts from accounts attributed to the Russian IRA were published, making it possible to conduct a detailed analysis of how Russia ran these information campaigns.\(^42\) The data showed that the campaign was not restricted to the 2016 US election but rather sought to divide online groups along racial, ethnic, social, and political lines, and continued long after the election was decided.\(^43\) Both sides of numerous controversial debates were inflamed by Russian IRA activity, especially conversations surrounding provocative race issues such as the Black Lives Matter movement in the United States.

**Measuring the effect of these information operations**

While the intention behind this activity is clear, measuring its impact is complex. Trolls have been shown to manipulate the opinions of users in online forums\(^44\) and to steer conversations on blogging platforms.\(^45\) While at times these accounts have garnered greater popularity than those of organic users,\(^46\) the impact they have on the wider online ecosystem is hard to measure. Some calculations show that Russian IRA accounts were influential in spreading targeted URLs across Twitter,\(^47\) but that this activity did not carry over to other web communities (Reddit, 4Chan).\(^48\) Twitter’s key role in these campaigns is also illustrated by the fact that in the run-up to the 2016 US Election, more hyperlinks to websites hosting disinformation were shared on Twitter than across the top sixteen mainstream media outlets combined.\(^49\) What is not clear from this evidence however, is what effect the Russian IRA accounts have had on more subtle areas such as promoting ideas in line with Russian interests, engaging other users to sway opinion, and fuelling both sides of controversial online discussions.


\(^{43}\) Gallacher and Fredheim, ‘Division Abroad, Cohesion at Home’; Linvill and Warren, ‘Troll Factories’. 


\(^{45}\) Anton Sobolev, ‘Fantastic Beasts and Whether They Matter: How pro-Government “Trolls” Influence Political Conversations in Russia’, *(In Prep)*.

\(^{46}\) Howard et al., ‘The IRA, Social Media and Political Polarization’.


In this paper we use a two-part strategy to measure the effect of information operations on online conversations. In Part 1 we focus on a case study of the Black Lives Matter (BLM) movement which was targeted by Russian IRA accounts. This social movement has spread both online and offline to protest the systematic violence perpetrated against African-Americans, particularly by police officers. Opposition movements to BLM (#BlackLivesMatter) have criticised it for failing to appreciate the value of all races (#AllLivesMatter) or for failing to respect the value of police officers and the risk they take in course of their work (#BlueLivesMatter). These hashtags can shape how information flows through the wider network and therefore play a significant role in the spreading of ideas. Russian IRA accounts imitated authentic users on both sides of this debate to disseminate provocative messages to various target audiences and to foster antagonism between opposing groups. This is likely to have contributed to the polarisation of the #BlackLivesMatter conversation online; Russian IRA accounts were in the top percentile of retweeted accounts in both supporting and opposing sides of the Twitter conversation. We investigated the global effect of the Russian IRA tweets on the entire #BlackLivesMatter conversation by testing whether the daily degree of polarisation of the Twitter conversation correlated positively with earlier Russian IRA activity surrounding the #BlackLivesMatter hashtag.

In Part 2 we look at the impact of Russian IRA activity on Reddit using natural language programming, text analysis measures, and causal impact modelling to analyse the effect of >16,000 Reddit posts attributed to the Russian IRA. Following revelations about the scope of Russian IRA manipulation of social media platforms in 2016, Reddit was the only social media company to keep this activity publicly visible on the platform rather than removing it, so it is the only platform where the immediate response to Russian IRA content can be analysed directly. We measure the response to known artificial activity and predict that

54 Stewart et al., ‘Examining Trolls and Polarization’.
Russian IRA activity causes a measurable decrease in the quality of discussion threads.

In this study we do not make any attributions to which accounts were operated from the Russian IRA. Instead the accounts were identified and attributed by the social media platforms themselves using information that is not available to the public.

**Methods**

*How does the degree of daily polarisation of the #BlackLivesMatter conversation on Twitter correlate with Russian IRA activity?*

**Data collection and sampling**

Twitter is a popular social media platform built on a microblogging format. Users can share short messages, or ‘tweets’, with their followers who can in turn ‘retweet’ these messages to their own followers. Tweets can sometimes contain hashtags indicating that it is part of a broader conversation. In late 2018 Twitter averaged 321 million active monthly users.²⁵

We obtained Twitter data relating to the Black Lives Matter conversation from an archive compiled by the digital chronicling organisation ‘Documenting the Now’ (DocNow).²⁶ The dataset contains 17,292,130 tweet IDs for tweets collected from the Twitter streaming API for #BLM and #BlackLivesMatter between 29 January 2016 and 18 March 2017.²⁷ Twitter’s terms of service do not allow public redistribution of tweets; however, they do allow datasets of tweet IDs to be shared. We then recovered the full tweet from each tweet ID by performing a search through the Twitter search API (also known as ‘hydration’) using DocNow’s Hydrator software.²⁸

Only tweets which were still publicly available at the time of the search could be recovered; we could not recover tweets that had been deleted by Twitter or by the users themselves.

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²⁶ Documenting the Now.
²⁸ DocNow Hydrator on GitHub.
We hydrated the dataset of tweet IDs on 24 November 2018, which led to a collection of 9,531,526 tweets, or 55% of available tweet IDs (45% of the original tweets had been deleted since publication). While our dataset, therefore, does not represent the full conversation, it is the best approximation available given the limits that Twitter places on data sharing. Importantly, this dataset does not contain the tweets from Russian IRA, as this information was removed from the platform at the point of attribution by Twitter, prior to collection. Therefore, our measure of polarisation reflects the polarisation of the conversation of genuine (i.e. non-Russian IRA) accounts without potential artificial inflation from Russian IRA tweets.

Data on the activity of known Russian IRA accounts were collected by Linvill and Warren⁵⁹, and made publicly available by the team at fivethirtyeight.com.⁶⁰ This dataset contains 2,973,371 tweets from 2,848 Twitter accounts spanning the period from 2015–2018.

Measuring polarisation

We measured the degree of daily polarisation on Twitter using a novel technique known as correspondence analysis, implemented in the FactoMineR package for R.⁶¹ Correspondence analysis is a statistical method that makes it possible to map contingency tables to expose underlying relationships between objects in the data.⁶² All analyses were performed in R (version 3.4.4, R Core Development Team 2017).

For each day of the dataset, we used a retweet matrix as the contingency table to show the relationship between active users within the dataset (rows) and popular tweets (columns) (see Table 1). A retweet matrix is a good starting point for discovering the structure of Twitter conversations as retweets have been shown to closely represent the expression of agreement with a particular message and, under certain conditions, support of the messenger.⁶³ Given this, we assumed that if a user retweets messages expressing support or opposition for a given position, this reflects the user’s own beliefs.

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⁶⁰ Oliver Roeder, ‘Why We’re Sharing 3 Million Russian Troll Tweets’, FiveThirtyEight, 31 July 2018.
Correspondence analysis interprets the retweet matrix across a number of dimensions whereby the largest amount of variability in the data is captured in dimension 1, the next largest amount of variability is captured in dimension 2, the third largest amount of variability is captured in dimension 3. The scores for dimension 1 were used to calculate the position of each tweet on the dimension 1 scale in relation to the other tweets for that day. As explained below, dimension 1 generally distinguishes between tweets that were either for or against the #BlackLivesMatter movement; the greater the score in dimension 1 the stronger the support or criticism. Opposition tweets were often framed as part of a counter-movement, such as #BlueLivesMatter, co-opting BLM-related hashtags (#BlackLivesMatter or #BLM) to inject opposing opinions into the conversation.

Table 1 and Figure 1 – Simplified retweet matrix for popular tweets and active users for the #BlackLivesMatter Twitter conversation on 07/07/2016 and the correspondence analysis results placing users on dimensions one and two.
We focused only on the dimension that demonstrated the greatest variance in the daily activity, dimension 1, because it was the most stable across multiple days and was the most reliable indication of the level of support or opposition for the Black Lives Matter movement indicated by the tweet. We verified the consistency of this dimension by taking a random sample of 50 days from the dataset and selecting the tweets with the highest and lowest scoring days on dimension 1. We manually coded whether the messages presented in these tweets represented opposing sides. This was the case for 85% of the days. Manual inspection of the remaining 15% of days showed that these tended not to have a polarised debate, and so the dimension was absent rather than missed.

To perform a successful a correspondence analysis, the contingency table had to represent a well-connected subgraph of the retweet network to avoid a small subset of users, peripheral to the main conversation, generating large scores on the important dimensions (similar to the k-core within network theory). We therefore used thresholds to filter out less popular tweets (as assessed by the number of retweets) and ‘inactive’ users (who did not retweet many popular tweets). These thresholds depend on daily conversation size and are shown in Table 2. After ranking all popular tweets along dimension 1, we used the results to estimate the dimension 1 score for each user compared to all other users, based on the average of all the tweets they had retweeted. This last step could be performed for all users, not only those defined as ‘active’ in the correspondence analysis.

Selecting the correct values for these thresholds is important for achieving stable results. We selected suitable thresholds dynamically for each day according to two rules: (a) thresholds should not produce extreme scores for a subset of users on dimension 1 ($|z| > 10$), and (b) when applying back to scores from the subgraph to all users, thresholds should allow for >25% of daily users in the conversation to be classified as belonging to dimension 1. In rare cases the standard thresholds did not fit; for these days slightly lower/higher thresholds were applied. This was necessary as for some days certain tweets went ‘viral’, changing the relationship between conversation size and the overall activity of the average user. While setting the thresholds appropriately improved results for each given day, taken overall changing these thresholds did not alter results substantially.

The distribution of users across dimension 1 reflects how their opinions are distributed, and whether users formed distinct ‘camps’—something
we would expect if the conversation were polarised. We were able to measure the degree of this polarisation using Hartigans’ dip test,\textsuperscript{64} which measures how bimodal a sample is, with higher scores indicating higher bimodality. We operationalised polarisation as the bimodality of each daily distribution of user scores on dimension 1 (Figure 2).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{network.png}
\caption{Figure 2(a) and (b) – Visualisation of the polarised retweet network and matching bimodal distribution for dimension 1 for the #BlackLivesMatter conversation on 07/07/2016}
\end{figure}

\textsuperscript{64} Martin Maechler, \textit{“Package “Diptest”}, CRAN, 5 December 2015.
Relation to Russian Troll Farm Activity

After measuring the degree of polarisation in the daily conversation from genuine accounts, we related it to the artificial activity originating from accounts associated with the Russian IRA using (lagged) Pearson’s correlations. Russian IRA activity is measured as the number of posts using a BLM-related hashtag from the public dataset released in summer 2018.

Russian IRA activity is unlikely to have an immediate effect on the degree of polarisation of the conversation, especially as the direct responses to this activity were unavailable. To measure the correlation between Russian IRA activity and the subsequent level of polarisation in the conversation, taking into account cumulative effects of sustained activity over time and delayed effects in the changing dynamics of the conversation, we compared the cumulative Russian IRA activity for a period of 1–7 days prior to each focal day in the dataset with the mean degree of polarisation over the subsequent 1–20 days.

To test if the association between Russian IRA activity and subsequent polarisation was significantly higher than expected by chance, we used a permutation test. For each given level of lag in polarisation (1–20 days) and cumulative period of Russian IRA activity (1–7 days), we simulated a new dataset where Russian IRA activity for each day was paired with a level of polarisation randomly sampled (with replacement) from our real dataset. We then calculated the correlation coefficient between the Russian activity and the lagged polarisation. This was repeated for 10,000 iterations. This circumvented the problem of autocorrelation associated with the lagged time-series as the lagged polarisation was calculated after the randomisation. To avoid biased coefficients arising from right-skewed distributions of activity and polarisation, we normalised the data using box-cox transformations in the R package ‘MASS’.

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We measured effect sizes for each cumulative period and lag period combination by taking the mean for the total 10,000 simulations. Significance values were calculated as the proportion of simulations where the simulated correlation was higher than the observed correlations.\textsuperscript{66}

Measuring the direct effect of Russian IRA activity on Reddit conversations

What is Reddit?

Reddit is a social media platform that focuses on news aggregation and discussion. Content is crowd-sourced, with members submitting text, images, or external hyperlinks, which are then voted up or down by other members. This content is organised into specific ‘subreddits’, user-created boards covering a wide variety of topics. In February 2018, Reddit had 542 million monthly visitors, ranking as the third most-visited website in the US and the sixth most-visited globally.\textsuperscript{67}

Data collection and sampling

Reddit released the identity of Russian IRA accounts in the summer of 2018. This totalled 16,821 Reddit posts from 944 accounts.\textsuperscript{68} We extracted our dataset in November 2018 from a publicly available repository of historical Reddit data on pushshift.io.\textsuperscript{69} The data are available in the form of a Google Big Query Database, which can be queried by users to download specific sections of the entire database. Here we study the period from January–December 2016, the period during which the Russian accounts were most active. We selected subreddits on which Russian IRA accounts posted at least 50 submissions during 2016. These span a range of topics, allowing us to explore differential effects in different areas of the social media platform. Previous research\textsuperscript{70} has demonstrated that some of these subreddits were used by the Russian accounts for political manipulation, while others were used for more mundane purposes such as generating realistic account histories or ‘karma’ (platform specific credits that give a user more credibility in their comments). We selected the followed

\textsuperscript{69} \url{https://files.pushshift.io/reddit/comments/}
\textsuperscript{70} Gallacher and Fredheim, ‘Division Abroad, Cohesion at Home’.
12 subreddits; r/funny, r/uncen, r/Bad_Cop_No_Donut, r/AskReddit, r/PoliticalHumor, r/news, r/worldnews, r/aww, r/gifs, r/politics, r/The_Donald, r/racism. Of these, the subreddit r/uncen had received only submissions from Russian IRA accounts and no comments on the posts and was therefore not included in the analysis. Pushshift collects data at the point that it is posted to Reddit. This means that the dataset is unaffected by subsequent deletion of posts, however it also means that it does not capture edits made to comments after they are posted (a feature available on Reddit but not on Twitter).

Text Analysis Measures

The impact of Russian IRA activity on the conversational quality on Reddit was operationalised using three text analysis measures, which were applied to each post included in the analysis: Integrative Complexity, Toxicity and Identity Attack.

Integrative Complexity (IC) is a social-psychological measure of how much an individual presents the ability to think and reason with input from multiple perspectives. Higher IC is associated with more accurate and balanced perceptions of other people, lower prejudice, the use of more information when making decisions, as well as less extreme views. Lower IC in discussions is associated with prediction of future violence and intergroup conflict. We used AUTO IC to get IC scores for each Reddit post. The system produces a score from 1 to 7 for each comment, with lower scores representing lower levels of complexity. AUTO IC has been used successfully for the study of online terrorist content, demonstrating the validity of applying the measure to the digital domain.

71 Pushshift, Reddit.
We measured the level of Toxicity of each Reddit post with the Google Perspective API. This classification tool was designed by Google’s ‘Project Jigsaw’ and ‘Counter Abuse Technology’ teams with the aim of promoting better discussions online. The tool uses machine learning models to score the perceived impact a comment might have on a conversation. Comments defined as being ruder, more disrespectful, or more unreasonable receive a higher Toxicity score. The model gives a Toxicity score for each comment on a scale ranging from 0 to 1.

The Google Perspective API also provides additional classifiers that are more specific and can provide further insight into the nature of comments. The Identity Attack option measures the degree to which a comment demonstrates negative or hateful comments targeting someone because of their identity. This is especially useful in the current study as it measures specific intergroup aggression and conflict based on who people are perceived to be. As with Toxicity, the model provides an Identity Attack score for each post on a scale ranging from 0 to 1.

Analysis of submissions and comments

Russian IRA activity consisted of submissions and comments. A submission is the starting post for a new conversation—i.e. threads started by Russian IRA accounts—while a comment is a post made on an existing conversation thread started by a genuine user. We analysed submissions and comments separately. We tested whether threads started by Russian IRA posts differed from those started by genuine users, and if Russian IRA comments injected into an existing thread had an impact on the subsequent conversation.

To measure the impact of submissions from Russian IRA accounts, we collected all comments made on threads started by Russian IRA accounts, including the initial submission starting the conversation, from the eleven subreddits identified above. In total this included 2,368 submissions and 30,112 comments. To test whether these conversations differed from genuine conversations, we collected a similar number of random ‘control’ submissions to the same subreddits within the same time frame. As with the Russian IRA submissions, we collected all the responses to this sample of genuine submissions, with a resulting total of 1,872

submissions and 22,503 comments. The lower number of genuine submissions is due to the exclusion of some submissions which received no subsequent comments. We then compared the conversation qualities for these two types of threads (those started by Russian IRA posts versus genuine submissions). As each subreddit was likely to include both types of conversation, we compared like-for-like conversations in each subreddit independently. For each comment in a thread we calculated a number of metrics relating to the measures used to determine the quality of the conversation, namely Integrative Complexity, Toxicity and Identity Attack.

To measure the impact of Russian IRA comments on existing genuine threads (rather than on new threads), we collected the comments from all threads that received at least one comment from a Russian IRA account. The sample of unmanipulated comment threads above was also used as the control for this sample. This dataset contained 455,300 comments from 826 threads, 1,253 of which came from Russian IRA controlled accounts. For each thread we numbered all comments in chronological order, with the injected Russian IRA post numbered as index position zero, subsequent posts incremented positively and previous posts negatively. We limited our analysis to threads containing ≥ 20 comments and to the 100 posts either side of the injected Russian IRA post. For each of these 200 comments we calculated the three text analysis measures and averaged these for each position in the thread across all threads, to show the average trend of the conversations. The data were then analysed using a causal analysis model (see details below) to detect changes in the three metrics after the injection of a Russian IRA comment. The analysis was performed across all subreddits for each metric. To explore whether the effect differed between political and non-political conversations, it was then run separately on political and non-political subreddits (Political_Subreddits; ‘The_Donald’, ‘politics’, ‘Bad_Cop_No_Donut’, ‘PoliticalHumor’, ‘racism’, ‘news’, ‘worldnews’, Other_Subreddits; ‘aww’, ‘gifs’, ‘funny’, ‘AskReddit’). We investigated both the immediate and the overall impact of a content injection by running the analysis on the first 25 comments as well as on all 100 comments post-injection.

Statistical Methods

We investigated differences between conversations started by Russian IRA accounts compared to controls by using linear mixed models (LMMs) with the lme4 package. We investigated differences in Integrative Complexity, Toxicity, and Identity Attack between the Russian IRA-started and genuine threads,
including subreddit ID as a random effect. Significance levels of fixed effects were obtained by comparing the full model to the null model with an $\chi^2$ test. The difference between Russian IRA-started and genuine threads was also compared in each of the 11 individual subreddits using Welch two sample $t$-tests comparing the differences in mean conversation qualities. Toxicity and Identity Attack measures were square-root-transformed to ensure normality. Integrative Complexity could not be normalised, and so a Wilcoxon rank sum test with continuity correction was used. We corrected for multiple comparisons by adjusting the p-values with a Bonferroni-Holm correction.

We calculated the impact of a single artificial comment on an existing thread using the CausalImpact() package for R.\(^79\) This package constructs a Bayesian structural time-series model to estimate the causal effect of a specific event on a time-series. In this case the time-series is the conversation quality (taken as the three text analysis measures) as it progresses over time along the thread, and the event is the Russian IRA comment injection at index position zero. This method allowed us to make causal inferences even though performing a randomised experiment was not possible. Through the construction of a time-series model this method predicts a counterfactual of how the response metric would have evolved after the intervention if the intervention had never occurred.\(^80\) This method requires a control time-series of similar data unaffected by the intervention—here we used the unmanipulated threads. By calculating the relationship between the control and response time-series trends on the 100 posts prior to the intervention, the model then predicted the response time-series over the subsequent 100 posts, had there been no injection of Russian IRA comment. We then calculated the observed pointwise differences between manipulated and predicted threads after the intervention occurred. Summing these pointwise differences over a given time window, the model could provide a measure of the size of this cumulative difference over time, which was tested for statistical significance with a Bayesian one-sided tail area probability test.

Results

Polarisation of Twitter conversations

Correlations between Russian IRA activity and subsequent polarisation of the Twitter conversation related to Black Lives Matter were significantly higher than expected by chance (permutation test, Figure 3b). This effect did not occur immediately following Russian IRA activity, but rather occurred predominantly between 3 and 10 days after the conversation manipulation had taken place. More specifically, it increased over time until reaching a peak around 7–9 days following the activity, and then gradually returned to the initial base level (Figure 3a). The effect started earlier, lasted longer, and was more pronounced when we considered Russian IRA activity over a longer time window (Figure 3, Table 3, see Table S1 for individual significance scores and correlation effect sizes). When looking at the longest period of cumulative activity—seven days—this trend appeared to last for almost two weeks from day two until day 14. Importantly, there was no general increasing or decreasing trend over time for either Russian IRA activity or polarisation and so our results were not due to long-term matching trends between the two variables.

The distributions of daily Russian IRA activity showed a long right tail (Appendix Figure 1c), suggesting this activity was uncommonly large on certain days. We tested whether these spikes in Russian IRA activity had an especially large effect on subsequent conversation polarisation by taking the top 10 days with the highest degree of polarisation, and testing whether each of these days had been preceded by a spike in Russian IRA activity (defined as a day with over 100 tweets) within a period of 10 days. We found that in 80% of these most polarised days, a spike in activity had preceded the polarisation.

The highest peaks in Russian IRA activity were fairly evenly distributed throughout the period studied. The mean Russian IRA activity across all days was 27 tweets, but this spiked as high as 592 tweets in a single day and 16 days had over 100 posts.

Reddit submissions

The conversation quality on threads started by Russian IRA-operated accounts differed substantially from that of genuine conversations, but the direction of these differences varied between subreddits and thus between topics of conversation. Overall, posts on threads started by Russian IRA accounts had higher Toxicity (IRA: 0.48 ± 0.001 vs genuine: 0.47± 0.002, $n = 56,249$, $\chi^2 = \ldots$
Figure 3(a-c) – a) Correlations between the degree of daily polarisation in BLM conversations on Twitter and preceding total Russian IRA Activity over various periods (1–7 days). Red dots show significant correlations.

b) Significance effects for max correlations for each activity window compared to distribution obtained by chance (grey) as calculated with a permutation test. (orange: p< 0.05, blue = non-significant)

c) Normalised distributions of polarisation and activity (see appendix for raw distributions)
<table>
<thead>
<tr>
<th>Number</th>
<th>Significant Days</th>
<th>Start Day (Lag)</th>
<th>End Day (Lag)</th>
<th>Day of Max Correlation</th>
<th>Max Correlation</th>
<th>P</th>
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<td>2</td>
<td>11</td>
<td>6</td>
<td>0.156</td>
<td>&lt;0.001</td>
</tr>
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</table>

Table 3 – Statistical results for the highest correlation in the lagged permuted test across each activity window. For full results see annex Table 1.

Figure 4(a-c) – Differences in mean conversation quality scores for threads started by Russian IRA Reddit accounts compared to genuine comment threads within the same subreddit. Higher values indicate Russian IRA started conversations scored higher on that conversation metric.
28.34, p < 0.001) and Identity Attacks (IRA: 0.42 ± 0.001 vs genuine 0.40±0.001, \( \chi^2 = 85.33, p < 0.001 \) but showed no overall change in Integrative Complexity (IRA: 1.37 ± 0.004 vs genuine 1.36 ± 0.004, \( \chi^2 = 2.39, p = 0.122 \)).

Further analyses performed on individual subreddits showed that threads started by Russian accounts within r/news, r/gifs, r/funny and r/Bad_Cop_No_Donut had higher average Toxicity scores than genuine threads in the same subreddits (Figure 4b, Table 4). Other subreddits showed no differences. We found a similar pattern with regard to levels of Identity Attack. Threads started by Russian accounts within r/racism, r/news, r/gifs, r/funny and r/AskReddit had higher average Identity Attack scores than genuine threads in the same subreddits (Figure 4c, Table 4), while artificial comment threads started within r/TheDonald by comparison had a lower average Identity Attack scores than genuine threads. Other subreddits showed no differences. While we found no difference in Integrative Complexity overall, artificial threads started by Russian IRA accounts received comments with lower IC scores in r/TheDonald and r/racism, but higher IC scores in r/PoliticalHumor, r/news, r/funny and r/AskReddit (Figure 4a, Table 4).

### Text Analysis Measures

<table>
<thead>
<tr>
<th>Subreddits</th>
<th>Integrative Complexity</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Toxicity</th>
<th></th>
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<th></th>
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<tr>
<td></td>
<td>Mean IRA Started</td>
<td>Mean Genuine</td>
<td>W</td>
<td>p</td>
<td>d</td>
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<td>Mean Genuine</td>
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<td>r/racism</td>
<td>1.18±0.02</td>
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<td>0.318</td>
<td>0.55±0.01</td>
<td>0.52±0.01</td>
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<td>r/The_Donald</td>
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<td>1.27±0.01</td>
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<td>0.38±0.01</td>
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<td>-1.11</td>
</tr>
<tr>
<td>r/gifs</td>
<td>1.41±0.03</td>
<td>1.43±0.02</td>
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<td>1</td>
<td>0.024</td>
<td>0.46±0.01</td>
<td>0.45±0.01</td>
<td>1023</td>
<td>1.06</td>
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<tr>
<td>r/worldnews</td>
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<td>1.23±0.01</td>
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<td>-5.22</td>
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<td>r/funny</td>
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<td>0.46±0.002</td>
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<tr>
<td>r/AskReddit</td>
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<td>-3.16</td>
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<tr>
<td>r/news</td>
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<td>0.149</td>
<td>0.43±0.01</td>
<td>0.42±0.01</td>
<td>2413</td>
<td>1.34</td>
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<tr>
<td>r/PoliticalHumor</td>
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<td>0.259</td>
<td>0.46±0.004</td>
<td>0.42±0.001</td>
<td>2143</td>
<td>4.75</td>
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</table>

Table 4 – Statistical results for paired sample t-tests comparing differences in mean conversation quality scores for threads started by Russian IRA Reddit accounts compared to organic comment threads within the same subreddit.
### Table 4 – Statistical results for paired sample t-tests comparing differences in mean conversation quality scores for threads started by Russian IRA Reddit accounts compared to organic comment threads within the same subreddit (continued)

<table>
<thead>
<tr>
<th>Subreddits</th>
<th>Mean IRA Started</th>
<th>Mean Genuine</th>
<th>df</th>
<th>t</th>
<th>p</th>
<th>d</th>
</tr>
</thead>
<tbody>
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<td>r/racism</td>
<td>0.61±0.01</td>
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<td>0.022</td>
<td>0.177</td>
</tr>
<tr>
<td>r/The_Donald</td>
<td>0.39±0.01</td>
<td>0.43±0.01</td>
<td>3792</td>
<td>5.5</td>
<td>&lt; 0.001</td>
<td>0.178</td>
</tr>
<tr>
<td>r/aww</td>
<td>0.29±0.01</td>
<td>0.30±0.01</td>
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<tr>
<td>r/worldnews</td>
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<td>991</td>
<td>-0.07</td>
<td>1</td>
<td>0.004</td>
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<td>r/gifs</td>
<td>0.36±0.003</td>
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<td>5208</td>
<td>-11.7</td>
<td>&lt; 0.001</td>
<td>0.314</td>
</tr>
<tr>
<td>r/politics</td>
<td>0.42±0.003</td>
<td>0.42±0.002</td>
<td>3766</td>
<td>0.5</td>
<td>1</td>
<td>0.012</td>
</tr>
<tr>
<td>r/Bad_Cop_No_Donut</td>
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<td>0.42±0.003</td>
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<td>-2.35</td>
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</tr>
<tr>
<td>r/AskReddit</td>
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<td>&lt; 0.001</td>
<td>0.314</td>
</tr>
<tr>
<td>r/PoliticalHumor</td>
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<td>735</td>
<td>-0.6</td>
<td>1</td>
<td>0.031</td>
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</tbody>
</table>

**Results – Reddit comments**

Across all subreddits and comment threads, Russian IRA comments led to a small drop in the Integrative Complexity of the subsequent conversation over a period of 100 comments by a factor of 1% ± 0.51 (Figure 5a-c).

For the period after a Russian IRA comment injection, the average Integrative Complexity was 1.41 ± 0.004. In the absence of any intervention, the causal analysis model predicted an average value of 1.42 ± 0.006, significantly higher than the observed value (Bayesian one-sided tail area probability \( p = 0.035 \)). In other words, on average a Russian comment caused a 0.01 decrease in IC compared to predictions.

Additionally, Russian IRA comment injections lead to short term increase in the Integrative Complexity of conversations in non-political subreddits by a factor of 2% ± 0.77 over the subsequent 25 comments \( (p = 0.005) \).
There were no measurable differences in the effect of Russian IRA comment injection on Integrative Complexity in political subreddits when considered in isolation, or in non-political subreddits over longer periods of time (Table 5).
Russian IRA comment injections also affected the Toxicity of subsequent conversations, but these effects occurred only in political subreddits and for short periods. While there was no significant effect of Russian IRA comment injection on Toxicity if considered over the entire post-intervention period of 100 comments, comment injections did increase Toxicity of the conversation over the next 25 comments by a factor of $3\% \pm 1.53 (p = 0.019)$, but this effect subsequently disappeared over the following 75 comments (Figure 6).

Similarly, the impact of the degree of Identity Attacks taking place in conversations after a Russian comment injection also depended on whether the comments occurred in political or non-political subreddits. In non-political subreddits, comment injection was followed by a marked short-term increase in Identity Attacks over the next 25 comments by a factor of $10\% \pm 2.04 (p = 0.001)$, and this effect subsequently dissipated over time. There was no change in the degree of Identity Attacks following a Russian IRA comment injection in a political subreddit.

![Figure 6 – Cumulative impact of artificial Russian IRA comment injections on the Toxicity, Identity Attack (IA), and Integrative Complexity (IC) of subsequent conversation on Reddit in political and non-political subreddits.](image)
Discussion

In this study we examined whether social media activity from artificial accounts run by the Russian IRA led to measurable changes in the conversation of genuine users on Twitter and Reddit. Our results show that Russian IRA activity indeed predicted changes in the conversations taking place on both platforms, but the exact effects differed between platforms and the type of manipulation taking place.

On Twitter, higher amounts of Russian IRA activity in the Black Lives Matter conversation predicted increases in the subsequent conversational polarisation of genuine Twitter users. This increase in polarisation peaked approximately one week after the injection of Russian IRA content and the association was most pronounced around the periods of highest Russian activity, suggesting that large spikes in Russian IRA activity had the greatest influence on the subsequent conversation. The gradual build-up of these effects over a week may reflect a structural property of Twitter—that more a tweet is retweeted, the more influence it gains on the network. On days with higher numbers of tweets from Russian IRA accounts there was a greater likelihood that one of the tweets would go ‘viral’ and be exposed to a much larger audience—either by simply manually increasing the number of tweets or by mass (automated) retweeting through the use of connected bot accounts. Earlier research has found that Russian IRA accounts embed themselves into both for and against sides of the Black Lives Matter debate, our results show that this may have contributed to the polarisation of both sides of the debate. It is noteworthy that we find this effect despite the high attrition rate within our Twitter data; 45% of Tweets were deleted before data collection. Deleted tweets are more likely to contain negative sentiment or profanity or to be ‘regretted’ by their author, and so the exclusion of these tweets likely muted the observed effects of Russian IRA activity on polarisation.

On Reddit we found that threads started by Russian IRA accounts were generally more Toxic than conversations started by genuine users whilst also showing more instances of Identity Attacks. Higher Toxicity reflects that these conversations

82 Kumar et al., An Army of Me’; Fredheim, ‘Robotrolling’.
83 Arif et al., ‘Acting the Part’.
were more rude, aggressive, or disrespectful, and more likely to inflame other users (both targets and observers), while conversations with higher Identity Attack scores contained a greater number of hostile comments made against people due to group membership, including race and political affiliation. Both of these measures indicate that Russian IRA activity was effective in promoting hostile conversations among other users, likely increasing divisions among group lines.

The effect of Russian IRA activity on Integrative Complexity was more complicated. While there was no overall difference in the Integrative Complexity of threads started by the Russian IRA compared to genuine threads, there were differential effects of Integrative Complexity depending on the subreddit in which a conversation was started. Conversations started by Russian IRA accounts in r/racism and r/The_Donald showed reductions in Integrative Complexity, (less complex conversations with less nuance, demonstrating reasoning from fewer viewpoints)\(^{87}\), while conversations started in r/AskReddit, r/funny, r/news and r/PoliticalHumor displayed higher Integrative Complexity compared to genuine conversation threads in these subreddits. One interpretation of these results is that they are related to the partisan nature of the political subreddits, which may facilitate a reduction in complexity due to a lack of opposing voices,\(^{88}\) compared to the ‘general interest’ subreddits, which may enable greater intergroup discussion because of their non-partisan nature. These and other explanations need direct testing, however, and merit further research.

We also found evidence suggesting a causal relationship between Russian IRA activity and conversation quality by studying the impact of comments from Russian IRA accounts injected into existing genuine conversations. Across all subreddits, Russian IRA comment injections led to a decrease in the Integrative Complexity of the conversation over the subsequent 100 comments. Additionally, there was a shorter-lived effect, detectable on the 25 subsequent comments, which led to an increase in Toxicity in political subreddits and an increase in the level of Identity Attacks in non-political subreddits. Although these findings are less clear-cut than those described above, they similarly demonstrate that any measurable effects of Russian IRA activity are in the direction of undermining conversational quality.Cumulatively, these small effects have the power significantly to shape a conversation. They also suggest that different dynamics unfold in political and

\(^{86}\)Google Project Jigsaw, *Perspective*; Wulczyn et al., *Ex Machina*.

\(^{87}\)Streufert and Suedfeld, *Conceptual Structure*.

non-political online conversations, which is in line with previous findings, and that distinguishing between these conversational domains remains important in future research. We found that in the absence of manipulation, the control threads within political subreddits had higher Integrative Complexity, Toxicity and Identity Attacks than non-political subreddits, suggesting that political conversations are characterised by both increased engagement and increased hostility. These characteristics may relate to findings that echo chambers form primarily in the political domain, but whether these are causes or effects remains to be tested.

Comparing the results across platforms, we found that the effects of Russian IRA activity manifested more quickly on Reddit than on Twitter. On average, the effects detected over 25 and 100 Reddit posts following manipulation peaked around 3.5 days and 5 days after submission respectively, while on Twitter the association between Russian IRA activity and polarisation peaked after 7 days. This is likely due to the structural differences between the platforms. On Twitter the impact of content is measured by popularity—how many people react to it—and therefore tweets that go viral can have a large effect on the overall conversation. On Reddit a single comment cannot go viral and impact results from the cumulative effect of many posts or of many users ‘upvoting’ a thread. On Twitter, tweets can take longer to go viral, compared to the direct responses which occur on Reddit threads, that have a shorter-lived visibility. Given these considerations, it would also be interesting to study the consequences of more sustained periods of Russian activity in a single Reddit thread. Our analytical procedure did not allow us to identify these consequences as we could only model a single intervention at a time, but we expect that repeated co-ordinated activity within a single thread would lead to increased cumulative effects. Including this co-ordinated behaviour may mean that the consequences of comments in existing threads more closely resemble the observed differences in total conversations following genuine submissions and Russian IRA submissions.

90 Barberá et al., ‘Tweeting From Left to Right’; Garimella et al., ‘Political Discourse on Social Media’.
By increasing the polarisation of conversations on Twitter and undermining the quality of conversations on Reddit, Russian IRA activity is likely to be effective in increasing the distance between social groups, fuelling both ideological and affective polarisation. This in turn provides ideal circumstances for the distribution of disinformation because it increases the acceptance of (inaccurate) information that confirms prior views—a phenomenon known as ‘confirmation bias’—and facilitates repeated exposure to the same inaccurate information because alternative perspectives are eliminated from discussion by design. Western societies that focus more on internal strife from polarised domestic communities tend to focus less on international issues, illustrating that this activity may be part of a larger geopolitical strategy.

In this study we focused on activity originating from publicly attributed Russian IRA accounts and their effect on two key social media platforms. Future research should consider including other platforms, and also other groups engaged in information operations. Russian IRA activity accounts for a fraction of all possible information operations activities worldwide, and many other groups produce similar content for a range of different purposes. This includes pursuing international strategic goals (as demonstrated by Iranian actions), focusing attention on perceived domestic concerns (utilised by far-right groups), and quashing dissent (a tactic favoured by China). Our study only begins to unveil the negative effect of information operations globally. If fuelling arguments on both sides of controversial topics works to increase polarisation in these conversations, then pushing only a single side may work to decrease polarisation or even to stifle active debate. This might be the goal for a regime that wishes to quash dissent or opposition. For example, evidence of Chinese government involvement in online discussions shows that across ~450 million social media posts per year the strategy is not to engage with controversial topics or with sceptics of government, but rather to change the subject.

94 Mason, ‘I Disrespectfully Agree’.
97 Pennycook et al., ‘Prior Exposure Increases’; Berinsky, ‘Rumors and Health Care Reform’.
99 Karan et al., ‘#TrollTracker’.
100 Nathaniel Gleicher, ‘Removing Coordinated Inauthentic Behavior from the UK and Romania’, Facebook Newsroom, 7 March 2019.
of conversations with vocal cheerleading for pro-China positions to overwhelm opposition voices. The Kremlin takes a similar approach towards domestic audiences, using troll farms such as the Russian IRA to produce vast quantities of pro-regime messages in Russian for local consumption.

While it remains to be seen whether these online effects translate into offline actions, there is evidence that online activities can have substantial effects on real world behaviour ranging from exercise and smoking to consumer trends. Our research also shows that online interaction between groups predicts offline violence, while other research demonstrates how online aggression towards disadvantaged groups can lead to offline hate crimes. By demonstrating that information operations promote social polarisation and can have measurable impacts on online conversations more broadly, our study also highlights the risk of potential future vulnerabilities. The ability of hostile actors to create polarising content is increasing at pace, thanks to advances in machine-generated text that closely resembles human speech. If this technology is paired with malicious intent to drive communities apart using social media platforms, then the volume of content may well expand and increase the severity of the challenge to detecting inauthentic content and oppose it.

It is therefore essential to design solutions that address and counter the negative effects of hostile information operations. Identifying the impact of information operations is only the first step in creating counter measures. Evidence suggests that organised attempts to challenge the veracity of disinformation on Twitter

103 Gallacher and Fredheim, ‘Division Abroad, Cohesion at Home’.
105 John David Gallacher, Marc W Heerdink, and Miles Hewstone, ‘Online Contact between Opposing Political Protest Groups via Social Media Predicts Physical Violence of Offline Encounters’, (under review), 1–44.
108 Miles Brundage et al., ‘The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation’, February 2018
are generally ineffective,\textsuperscript{109} while spontaneous fact-checking on Facebook is rare and generally unsuccessful.\textsuperscript{110} Other technical solutions should therefore focus on the early detection of artificial content before it can manipulate online conversations,\textsuperscript{111} or educational methods which may mitigate the effects of disinformation through inoculation of citizens.\textsuperscript{112} Structural changes to social media platforms promoting positive exposure to members of opposing groups will also likely reduce and dilute the impact of efforts to divide these same groups through negative content injections.\textsuperscript{113} Addressing the challenge of disinformation is so broad that designing effective interventions will require interdisciplinary efforts at multiple levels of analysis.\textsuperscript{114}

Conclusion

Our study reveals that the malicious use of social media by ‘fake’ accounts can measurably affect the subsequent conversations held by genuine users. Using the activity of the Russian Internet Research Agency on Twitter and Reddit as case studies, we have shown that this effect differed between social media platforms. The effect of Russian activity on Twitter was to increase polarisation after a one-week delay, while there was a more immediate effect on Reddit, immediately altering the quality of subsequent conversations. By developing methods to measure the impact of information operations in online conversations, our study provides an important step in developing effective countermeasures.

Acknowledgements

This research was supported by grants from EPSRC and the University College Oxford Radcliffe Scholarship. The second author’s contribution to this project was partially supported by a grant from the Netherlands Organisation for


\textsuperscript{111} Jordan Wright and Olabode Anise, ‘Don’t @ Me: Hunting Twitter Bots at Scale’, \textit{Black Hat}, 2018, 1–43.


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### Table Appendix 1 – Statistical results for the lagged permutation test across activity window and lag period. Bold indicates statistical significance at the p = 0.005 level

<table>
<thead>
<tr>
<th>Sum Period (Days)</th>
<th>Lag Period (Days)</th>
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<th>p</th>
</tr>
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<tbody>
<tr>
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<td>0.419</td>
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<tr>
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