A Comparative Study of Online Disinformation and Offline Protests

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Abstract. In early 2021 the United States Capitol in Washington was stormed during a riot and violent attack. A similar storming occurred in Brazil in 2023. Although both attacks were instances in longer sequences of events, these have provided a testimony for many observers who had claimed that online actions, including the propagation of disinformation, have offline consequences. Soon after, a number of papers have been published about the relation between online disinformation and offline violence, among other related relations. Hitherto, the effects upon political protests have been unexplored. This paper thus evaluates such effects with a time series cross-sectional sample of 125 countries in a period between 2000 and 2019. The results are mixed. Based on Bayesian multi-level regression modeling, (i) there indeed is an effect between online disinformation and offline protests, but the effect is partially mediated by political polarization. The results are clearer in a sample of countries belonging to the European Economic Area. With this sample, (ii) offline protest counts increase from online disinformation disseminated by domestic governments, political parties, and politicians as well as by foreign governments. Furthermore, (iii) Internet shutdowns tend to decrease the counts, although, paradoxically, the absence of governmental online monitoring of social media tends to also decrease these. With these results, the paper contributes to the blossoming disinformation research by modeling the impact of disinformation upon offline phenomenon. The contribution is important due to the various policy measures planned or already enacted.

Keywords: Propaganda, misinformation, fake news, Internet filtering, multi-level regression, comparative research, media freedom, freedom of expression

1 Introduction

Recently, Piazza (2021) published an intriguing study on the relationship between online disinformation and domestic terrorism. According to his result, disinformation spread by governmental actors and political parties contributes to domestic terrorism but the effect is mediated by political polarization and tribalism within countries. Rather similar results were recently obtained also by Gallacher et al. (2021) according to whom discussions in social media between opposing groups are associated with offline physical violence. Also Arayankalam
and Krishna (2021) showed that disinformation spread by foreign actors is associated with physical violence. A relation has been also found between online hate speech and offline hate crimes (Williams et al. 2020). Recently, Diab et al. (2023) found that white supremacist online propaganda tends to later appear offline in the form of fliers, banners, and graffiti. Closer to the present study, Kirkizh and Koltsova (2021) further found that exposure to online news is positively associated with participation in political demonstrations, including particularly in authoritarian countries. While there is thus a solid foundation for the present work, thus far, the relation between online disinformation and offline political protests has not been explored. This gap in existing research is surprising already due to the studies exploring the relation of online phenomena to violence, which is a much stronger presumption than a mere political protest.

It has been widely observed that the Internet and social media increase political activity due to the ease of exchanging information and recruiting new members for a common cause, emotional and motivational appeals, strengthening of group identities, agenda-setting and empowerment, and related factors (Berman 2018; Brunsting and Postmes 2002; Jost et al. 2018; Schumann 2015, pp. 22–36; Willnat et al. 2013). The perhaps most often cited example is the Arab Spring in the 2010s during which social media was successfully exploited for uprisings and other political purposes. According to empirical results, indeed, coordinated posts in social media increased the volume of protests the next day (Steinert-Threlkeld et al. 2015). Though, paradoxically, despite all the bells and whistles, there are also studies indicating that maintaining social media presence may decrease political participation (Theocharis and Lowe 2016). In terms of social movements, keeping an online movement alive for offline action is always a challenge (Bu 2017). According to skeptical viewpoints, the weak ties of online engagement lack power and seldom lead to new political possibilities (Unver 2017). If nothing else, these critical results and skeptical viewpoints serve to underline that much still remains unknown about online politics and their relation to offline activities.

The same applies to disinformation research (Guess and Lyons 2020). Here, too, again, the Arab Spring serves as an important but sombre historical milestone. The early enthusiasm about the Internet’s democratizing power soon after changed into a disillusionment. First came ISIS, then came Brexit, and later came the 2016 and 2020 presidential elections in the United States. All four examples are also important landmarks of disinformation and its research. As is soon further discussed in Section 2, the examples also underline a state-centric viewpoint to disinformation; ISIS was skillful with propaganda, as was Russia with its alleged foreign election interference in the United States and elsewhere. Although it has been questioned how successful Russia was in its past election interference endeavors (Eady et al. 2023), it can be still acknowledged that at least they were skillful. Also other actors—from political parties to charlatans—quickly learned how the online disinformation game is played in the current algorithmically cu-

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1 Islamic State of Iraq and the Levant (ISIS).
rated and platform-dominated information ecosystems (Bradshaw 2020). Given this brief motivating introduction, the paper examines the following hypothesis:

* A hypothesis: online disinformation disseminated by governments, political parties, and politicians, whether to domestic or foreign audiences, is associated with offline political protests, either decreasing or increasing the frequency of these, possibly via mediation with other political phenomena such as political polarization.

For examining the hypothesis, the paper proceeds in a straightforward manner. To further sharpen the hypothesis, the paper’s framing is first elaborated in more detail in Section 2. Thereafter, the research design is discussed in Section 3, the empirical results are presented in Section 4, and the conclusion follow in the final Section 5.

## 2 Framing

The online and offline realms increasingly intervene, and this poses major challenges to democracy and civil rights (Ruohonen 2021b; Unver 2017). Disinformation is among these challenges. In the past—not so long ago, a propagandist eager to spread disinformation had to have a printing press to publish books containing false information, an airplane from which to drop leaflets, or a television channel via which disinformation could be broadcast to masses. But those days are long gone. The Internet and its algorithms make propagation of disinformation easy.

A few words must be written about terminology, which is still debated in academia and elsewhere (Altay et al. 2023; Choraśa et al. 2021; Guess and Lyons 2020; Horne 2021). There is a good reason for these debates; it is difficult to make demarcations between disinformation, misinformation, propaganda, fake news, hoaxes, conspiracy theories, satire, memes, deep fakes, and whatever else the Internet and its subcultures continuously invent—together with intelligence agencies and other governmental bodies. Nevertheless, to make at least some sense out of the terminological confusion, misinformation can be defined as an unintentional adaption or dissemination of false or inaccurate information; conspiracy theories and related phenomena belong to this category. Disinformation, in turn, can be seen to involve intentional propagation of information that is known to be false or misleading in order to reach specific goals. Here, intention is the keyword; disinformation is a weapon particularly in the hands of governmental bodies and political actors. But, then, so is propaganda, which, however, can be conceptually separated from disinformation because propaganda may also deliver information that is true. While keeping these points in mind, the dataset used defines disinformation simply as “misleading viewpoints or false information.” Given that this simple characterization may also refer to misinformation, propaganda, or something else, the choice to prefer the term disinformation is somewhat misleading but can be justified on the grounds that the theoretical
hypothesis presumes an intention to provoke offline political protests. For any empirical purposes, the choice of a term does not matter.

Furthermore, the term disinformation should be, in the present context, prefixed with the term state-centric. There are three reasons for this additional qualifying term, which generally refers to actions and policies of states in a contrast to actions and policies of other actors, including private sector actors, international but not multilateral organizations, non-governmental organizations, and related actors operating in the online environment. The first reason is practical; the dataset used specifically includes only variables on disinformation that is disseminated by actors explicitly tied to countries’ political systems. This framing aligns with other recent studies that have examined counter-propaganda efforts by state-affiliated organizations (Ruohonen 2021a). The second reason originates from the comparative research approach pursued; here, the term state-centric is often used to distinguish research operating with inter-state relations in a contrast to multi-level or global perspectives (Ebbinghaus 1998). The third and final reason relates to the dependent variable. As is soon clarified in Section 3.2, the disinformation variables are regressed against a variable that measures protests against a state or its policies. Together, these terminological clarifications also sharpen the underlying hypothesis.

The disinformation and propaganda disseminated by ISIS and Russia have had one thing common; the primary (but not the only) target has been Western democracies, and the intention has been to deepen the existing societal cleavages and sabotage the internal cohesion within Western countries by exploiting weaknesses in the current engagement economy and conducting violent offline attacks, whether via terrorism or assassinations (Dundon and Houck 2022; Hamilton 2019; Kalniete and Pildegovičs 2021; Rosenblatt et al. 2019; Sultan 2019; Zhang et al. 2021). Hate is a powerful method, whether in the hands of Muslim minorities or right-wing extremists.

To reach the goals, which, as said, are a distinct trait of disinformation, time and sufficient resources are needed. In a sense, one still metaphorically needs the printing press, the airplane, or the television channel; to exploit societal weaknesses, one needs to be well-educated. The same applies when the goal of the exploitation is to provoke political protests in foreign countries. Education, staffing, and resources are thus another factor separating state-centric disinformation from other false information propagated by laymen. Though: if the online and offline realms intervene, so do the old logic and the new logic of media; many national disinformation outlets, some of which are linked to foreign disinformation organizations, rely on national media for their criticism and distortion of narratives (Toivanen et al. 2021). For building such disinformation outlets, nevertheless, time is needed even when the result would be amateurish due to lack of education.

Time is important also methodologically; many of the studies exploring the online-offline nexus have relied on cross-sectional data or survey snapshots, although a longitudinal focus too is necessary. Finally, time, resources, and skill are needed also by political parties and politicians who rely on false informa-
tion in order to reach political goals via the emotionally driven information ecosystems (Ruohonen 2020). To conclude: the framing described aligns with the longitudinal cross-country analysis pursued. The design for the analysis is thus subsequently elaborated.

3 Research Design

3.1 Data

Three datasets are used for the empirical analysis. The first is the mass protest dataset assembled by Clark and Regan (2016b). It provides the dependent variable for the analysis. The primary independent variables for disinformation are based on the celebrated V-Dem dataset (Coppedge et al. 2021b). Also the secondary independent variables come from the same dataset. Finally, two control variables were retrieved from World Bank’s (2021a; 2021b) online data portal. The datasets were merged by including only those countries that were present in all datasets with no missing values. Although merging reduced the number of countries—from 162 in the protest dataset to \( n = 125 \) in the sample used, the absence of missing values outweigh the reduction and the use of interpolation techniques. It is also worth noting that, for a reason or another, the protest dataset misses the United States, which is a clear limitation in the present disinformation context. Given that there are \( t = 20 \) years for each country, covering a period from 2000 to 2019, the sample size is still more than sufficient for statistical analysis.

3.2 Dependent Variable

The protest variable measures a gathering of at least fifty people who oppose a state or its policy in a given country. As clarified by Clark and Regan (2016a), the variable excludes (a) protests opposing a foreign state or a group of states as well as (b) demonstrations with non-state targets, including socioeconomic, religious, or other groups protesting rival groups—even when these have required intervention from police forces. Moreover, (c) industrial action only counts as a protest if people protest outdoors for a state-level labor policy instead of protesting against a company or an employer association. Finally, (d) armed resistance and rebel groups are excluded. All in all, the dependent variable thus measures conventional political protests against a state or the policies it has enacted or is about to enact. As for operationalization, the individual protests reported in the dataset were aggregated into annual counts. As can be seen from the outer beanplot in Fig. 1, and the inner histogram and density plot, the result is a typical count data variable; there are many country-year pairs with no protests but the distribution has a long right tail.
3.3 Independent Variables

The primary independent variables are obviously related to disinformation. There are five variables in the V-Dem dataset for disinformation. All of these have been used in recent research (Arayankalam and Krishna 2021; Piazza 2021), and all of these are used also in the present work.

The first two measure whether and how often a government, its agencies, and agents working on its behalf disseminate disinformation on social media for domestic and foreign audiences. These two variables on governmental disinformation dissemination are ideal for examining the state-centric viewpoint. Although neither variable considers the context and content of the disinformation spread, the distinction between domestic and foreign audiences aligns with war propaganda, which is often exported to foreign consumption and designed for domestic audiences in order to counter war weariness and related concerns (Ruohonen 2021a). Certainly, disinformation is propagated online also by numerous other non-governmental entities; fortunately, therefore, V-Dem provides also analogous two variables regarding the frequency of disinformation distributed to domestic and foreign audiences by major political parties and political candidates. Again, the distinction between domestic and foreign audiences is important because political parties in one country may disseminate false information to another country (Ruohonen 2020). The Internet makes such dissemination easy. The fifth variable is about imported disinformation; whether a foreign government and its lackeys have targeted a given country with their exported disinformation. Needless to say, the alleged election interference by Russia and other countries provides a solid rationale also for this variable.

Six independent variables are included for capturing the policy-side. A few examples are in order to contextualize this side. Although heavily criticized (Schulz 2020), the Network Enforcement Act (NetzDG) in Germany is a good example...
of legislative attempts to filter online hate speech. Likewise, in 2018, a comparable law was passed in France; it allows public authorities to remove fake information or even block sites that publish such content (Nagasako 2020). In addition to these national laws, the European Union has been actively enacting different legislative measures and informal codes of conduct, including for disinformation and hate speech (Buiten et al. 2020; Pataki et al. 2021). On the side of even more drastic measures, particularly authoritarian countries in conflict zones have increasingly resorted to Internet shutdowns; among the memorable historical examples was the 2011 shutdown of the Internet in Egypt in the face of the Arab Spring uprisings (Arnaudo et al. 2013). Thus, there is a well-founded rationale to consider also the policy-side variables.

The six variables are: (1) the capacity of a government to filter online content; (2) governmental filtering of online content in practice; (3) the capacity of a government to shutdown national parts of the Internet; (4) governmental alternatives to global social media platforms; (5) governmental monitoring of social media; and (6) regulation of online content (Coppedge et al. 2021a, pp. 317–320). All variables are standardized akin to $z$-values; a value zero approximates the mean of all country-year pairs in the V-Dem dataset. For the capacity-related variables (1) and (3), higher values indicate a higher capacity of the measures taken. For the variables (2) and (5), higher values indicate that a government neither censors online political information nor monitors social media for political content. For the variable (4), higher values indicate that people seldom use state-controlled social media platforms. Finally, for the variable (6), higher values indicate that a government can only remove content based on well-defined legal criterion.

To align the present work with Piazza’s (2021) paper, an independent variable is included for political polarization. Unlike measures and conceptualizations based on political parties and national party systems (Lauka et al. 2018; Sartori 1976), the political polarization variable in the V-Dem dataset is a composite variable measuring “the extent to which political differences affect social relationships beyond political discussions,” such that in polarized societies “supporters of opposing political camps are reluctant to engage in friendly interactions, for example, in family functions, civic associations, their free time activities and workplaces” (Coppedge et al. 2021a, p. 224).3 Although the United States is not present in the sample used, the country is currently the best known example of such society-wide political polarization.

### 3.4 Control variables

Four control variables are used: a change in a country’s governing regime type, the presence and consumption of national online media, a country’s gross domestic product (GDP) in current prices (World Bank 2021a), and the total pop-

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3 The names of the independent variables in the V-Dem dataset are: v2smgovfilcap, v2smgovfilprc, v2smgovshutcap, v2smgovsmalt, v2smgovsmmon, v2smregcon, and v2cacamps, in the order of listing.
ulation in a country (World Bank 2021b). The last two control variables were used also by Piazza (2021).

The first control variable is a re-coded dummy variable indicating whether a country’s past regime changed for any reason in a given year, whether due to a loss in a war, a coup d’état, an assassination, a popular uprising, a civil war, a democratization process, a foreign interference, or something analogous (Coppedge et al. 2021a, p. 134). If the current regime is still in place, the dummy variable takes a value zero. Although the dummy variable is included only as a control variable, such that no theoretical interpretation is provided for its potential statistical effect, there is still a rationale for its inclusion; it is highly probable that a regime change leads to protests and increased political activity both online and offline. The final control variable is the existence of national online media and its consumption by domestic audiences.4

3.5 Methods

The dependent variable represents the count of protests in a given country in a given year. Given that no protests occurred in about one-third of the country-year pairs, a conventional zero-inflated Poisson model is used for statistical estimation of the protest counts. In general, the model is a standard Poisson regression that additionally takes into account the overdispersion caused by the zeros.

Unlike Arayankalam and Krishna (2021), who only consider cross-sectional estimates in a single year, the estimation is carried in a time series cross-sectional (TSCS) context, which is a natural choice due to the underlying panel data. The TSCS context offers some clear benefits. Among these is the sample size; in total, \( n \times t = 20 \times 125 = 2500 \) observations are present. Another benefit is the possibility to evaluate and control the longitudinal dynamics together with the cross-sectional dimension. There are also specific statistical estimators that take the longitudinal dimensions into account (Arellano and Bond 1991). Instead of considering such dynamic estimators, however, the model specifications are kept as simple as possible due to the large number of variables; the estimation is carried out with so-called random effects models in which the cross-sectional and annual effects are modeled with varying intercepts. In other words, there are intercepts for both countries and years, and these are modeled as random variables. This simple specification is well-known and well-documented (Wooldridge 2010). As the interest is only to control and not interpret the annual and cross-sectional effects, the random effects model is preferable—insofar as the effects are statistically relevant (Antonakis et al. 2019). As for computation, Bayesian estimation is used with the \texttt{brms} package (Bürkner 2017), which provides a user friendly R interface for the Stan machinery.

Three models are estimated. The first includes the five governmental disinformation variables; the second the two party disinformation variables; and the

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4 The two control variables are named \texttt{v2monex} and \texttt{v2regendtype} in the V-Dem dataset, respectively.
third all of the variables. The four control variables are included in all models. Following the arguments that comparative research should focus on different regimes, alliances, and unions of countries (Ebbinghaus 1998), the models are further recomputed with a subset of 26 countries belonging to the European Economic Area (EEC). This additional computation provides a good re-check of the results because the EEC region is well-defined instead of being a pseudo-random sample of countries in the world. Finally, interactions between the variables are briefly considered, as in previous research (Piazza 2021; Arayankalam and Krishna 2021), but these are described later alongside the analysis.

4 Results

The multi-level regression results are summarized Tables 1 and 2. These can be disseminated with three points. Before proceeding, it is worth remarking that the standard deviations are fairly large for both the annual and the cross-sectional random effects. The model specification thus seems adequate in this regard. The cross-sectional variances are also larger than the annual variances. The overdispersion parameters too are clearly non-zero.

First, a surprise is immediately present; in all three models, all of the coefficients for the governmental disinformation variables have negative signs in the full sample containing all $n = 125$ countries. The same applies for the two party disinformation variables, which, however, have coefficients with positive signs in the third model. The magnitudes of the coefficients for the disinformation variables are also relatively modest. In contrast, in the EEC sample all of the disinformation variables align with prior expectations; in the third full model, for instance, positive signs are present for coefficients measuring governmental propagation of disinformation to domestic audiences, disinformation spread by foreign governments, and domestic disinformation disseminated by political parties and major political figures. Negative signs, in turn, are present for disinformation exported to foreign audiences, whether done by governmental bodies or political parties. Thus, it seems that if a government or a political party in the EEC region is engaged in the dissemination of disinformation to foreign audiences, there is less domestic political protests in the given country. While it is difficult to interpret such negative effects upon the protest counts, counter-disinformation by national security organizations may offer a partial explanation (cf. Nakissa 2020; Ruohonen 2021a). The coefficients are also relatively large in magnitude for all disinformation variables in the third model for the EEC sample. The discrepancy between the two samples becomes more evident when looking at the conditional effects shown in Figs. 2 and 3. As can be seen, the effects in the EEC sample are indeed forceful.

Second, similar mixed results are present for the policy variables. In the full sample the coefficients have negative signs for the variable on the government capacity for Internet shutdowns. The negative effects are also large when compared to rest of the policy variables (see Fig. 2). This observation can be interpreted to imply that such shutdown measures are effective in decreasing offline protests.
### Table 1. Regression Results: Full Sample (20 years, 125 countries)

|                         | Model 1             | Model 2             | Model 3             |
|-------------------------|---------------------|---------------------|---------------------|
|                         | 95% CI 1            | 95% CI 2            | 95% CI 3            |
|                         | Coef. lower upper   | Coef. lower upper   | Coef. lower upper   |
| Intercept               | −2.59 −4.69 −0.43  | −2.69 −4.83 −0.53  | −2.91 −4.92 −0.88  |
| Gov. disinformation: domestic | −0.17 −0.26 −0.09  | −0.10 −0.19 0.00   |                     |
| Gov. disinformation: abroad | −0.11 −0.21 −0.01  | −0.10 −0.21 0.02   |                     |
| Foreign gov. disinformation | −0.07 −0.16 0.02   | −0.07 −0.16 0.02   |                     |
| Party disinformation: domestic | −0.13 −0.21 −0.05  | 0.02 −0.07 0.10    |                     |
| Party disinformation: abroad | −0.10 −0.18 0.00   | 0.06 −0.05 0.16    |                     |
| Gov. filtering capacity  | 0.10 0.00 0.20      |                     |                     |
| Gov. filtering practice  | 0.05 −0.05 0.15     |                     |                     |
| Gov. shutdown capacity   | −0.18 −0.28 −0.07   |                     |                     |
| Gov. social media alternatives | 0.03 −0.10 0.16    |                     |                     |
| Gov. social media monitoring | −0.20 −0.29 −0.10  |                     |                     |
| Regulation of online content | 0.09 −0.01 0.19    |                     |                     |
| Political polarization   | 0.16 0.11 0.21      |                     |                     |
| National online media    | 0.01 −0.05 0.07     | 0.01 −0.05 0.07    | −0.02 −0.08 0.05   |
| Regime change            | −0.03 −0.13 0.06    | −0.01 −0.11 0.08   | 0.01 −0.09 0.11    |
| ln(population)           | 0.35 0.23 0.48      | 0.35 0.23 0.47     | 0.36 0.24 0.48     |
| ln(GDP per capita)       | −0.25 −0.33 −0.16   | −0.24 −0.32 −0.16  | −0.23 −0.31 −0.14  |
| Std. dev. years (intercepts) | 0.29 0.20 0.42    | 0.29 0.20 0.43     | 0.27 0.18 0.39     |
| Std. dev. countries (intercepts) | 1.07 0.91 1.24 | 1.00 0.86 1.16     | 0.99 0.84 1.17     |

### Table 2. Regression Results: EEC Sample (20 years, 26 countries)

|                         | Model 1             | Model 2             | Model 3             |
|-------------------------|---------------------|---------------------|---------------------|
|                         | 95% CI 1            | 95% CI 2            | 95% CI 3            |
|                         | Coef. lower upper   | Coef. lower upper   | Coef. lower upper   |
| Intercept               | −4.87 −14.05 3.25   | −4.33 −12.22 2.87   | −2.55 −14.12 7.75   |
| Gov. disinformation: domestic | 0.13 −0.06 0.32    | 0.47 0.17 0.76      |                     |
| Gov. disinformation: abroad | −0.74 −1.04 −0.43  | −0.61 −0.99 −0.21   |                     |
| Foreign gov. disinformation | 0.38 0.18 0.59     | 0.61 0.34 0.88      |                     |
| Party disinformation: domestic | 0.07 −0.11 0.25    | 0.61 0.34 0.88      |                     |
| Party disinformation: abroad | −0.80 −1.06 −0.56  | −0.62 −0.96 −0.28   |                     |
| Gov. filtering capacity  | 0.12 −0.34 0.59     |                     |                     |
| Gov. filtering practice  | −0.51 −0.94 −0.06   |                     |                     |
| Gov. shutdown capacity   | −0.05 −0.56 0.48    |                     |                     |
| Gov. social media alternatives | 0.69 0.19 1.22    |                     |                     |
| Gov. social media monitoring | −0.38 −0.65 −0.10  |                     |                     |
| Regulation of online content | −0.38 −0.65 −0.10  |                     |                     |
| Political polarization   | 0.49 0.28 0.71      |                     |                     |
| National online media    | 0.48 0.30 0.65      | 0.35 0.17 0.52      | 0.33 0.12 0.53      |
| Regime change            | −0.28 −3.65 3.10    | −1.08 −3.94 1.79    | −2.15 −6.52 2.15    |
| ln(population)           | 0.47 0.00 1.00      | 0.59 0.19 1.05      | 0.45 −0.16 1.14     |
| ln(GDP per capita)       | −0.15 −0.45 0.15    | −0.36 −0.66 −0.07   | −0.28 −0.60 0.03    |
| Std. dev. years (intercepts) | 0.34 0.23 0.50    | 0.35 0.23 0.51      | 0.27 0.18 0.40      |
| Std. dev. countries (intercepts) | 1.63 1.15 2.28 | 0.35 0.23 0.51      | 2.07 1.42 3.06      |
Fig. 2. Conditional Effects: full sample (Model 3, excluding control variables and random effects, 95% CIs)
Gov. disinformation: domestic (1)
Protests
−1 0 1 2
0 2 4 6 8 10
Gov. disinformation: abroad (2)
Protests
−1 0 1 2
0 2 4 6 8 10
Foreign gov. disinformation (3)
Protests
−3 −1 1 3
0 2 4 6 8 10
Party disinformation: domestic (4)
Protests
−1 0 1 2
0 2 4 6 8 10
Party disinformation: abroad (5)
Protests
−1 0 1 2
0 2 4 6 8 10
Gov. filtering capacity (6)
Protests
−2.0 −0.5 1.0
0 2 4 6 8 10
Gov. filtering practice (7)
Protests
−3 −1 1 3
0 2 4 6 8 10
Gov. shutdown capacity (8)
Protests
0.5 1.5
0 2 4 6 8 10
Gov. social media alternatives (9)
Protests
0.5 1.5 2.5
0 2 4 6 8 10
Gov. social media monitoring (10)
Protests
0.5 1.5 2.5
0 2 4 6 8 10
Regulation of online content (11)
Protests
−3 −1 1 3
0 2 4 6 8 10
Political polarization (12)
Protests
−1 1 2 3 0 2 4 6 8 10

Fig. 3. Conditional Effects: EEC sample (Model 3, excluding control variables and random effects, 95% CIs)
### Table 3. Regression Results in Two Polarization Regimes (coefficients)

|                               | Full Sample | EEC Sample |       |       |
|-------------------------------|-------------|------------|-------|-------|
|                               | Low polar.  | Low polar.  | High polar. | High polar. |
| Intercept                     | −0.98       | −4.84      | 1.79   | −18.46|
| Gov. disinformation: domestic | 0.41        | −0.35      | −0.14  | 0.24  |
| Gov. disinformation: abroad   | −0.47       | 0.04       | 0.58   | −0.48 |
| Foreign gov. disinformation   | 0.53        | −0.28      | < 0.01 | 0.53  |
| Party disinformation: domestic| −0.47       | 0.16       | −1.25  | 0.48  |
| Party disinformation: abroad  | 0.51        | −0.29      | −1.06  | −0.98 |
| Gov. filtering capacity       | −0.06       | 0.15       | 0.15   | −0.69 |
| Gov. filtering practice       | −0.18       | 0.17       | 0.68   | 0.07  |
| Gov. shutdown capacity        | −0.95       | −0.03      | 0.32   | 0.82  |
| Gov. social media alternatives | 0.29        | −0.04      | −0.65  | 0.55  |
| Gov. social media monitoring  | −0.60       | −0.07      | −0.21  | −0.38 |
| Regulation of online content  | −0.71       | 0.36       | −0.25  | −0.45 |
| National online media         | 0.16        | −0.03      | −0.11  | −0.01 |
| ln(population)                | 0.26        | 0.46       | 0.57   | 0.88  |
| ln(GDP per capita)            | −0.23       | −0.20      | −0.59  | 0.67  |
| Std. dev. years (intercepts)  | 0.21        | 0.26       | 0.57   | 0.47  |
| Std. dev. countries (intercepts) | 1.83 | 0.99       | 2.40   | 2.10  |

Although such measures are highly controversial, the causal effect in itself seems logical. In contrast, there is also a strong negative effect for the variable measuring governmental online monitoring of political content in social media. By recalling the scale of this variable, it seems that the absence of such monitoring decreases offline protest counts, which seems somewhat illogical. Similar observations can be made from the EEC estimates, although with this sample the conditional effects are small in magnitude (see Fig. 3). Such small effects could be used to argue that controversial measures such as NetzDG are not effective in reducing offline protests. Neither does the capacity for Internet shutdowns decrease the offline protest counts in the EEC sample.

Last but not least, there is a substantial positive effect of political polarization upon the protest counts. The result is hardly surprising as such; the more there is polarization, the more there are protests—the logic is sound. But what remains unclear is whether polarization further mediates the effects of the disinformation variables particularly in the full sample. This is the argument recently put forward by Piazza (2021) with respect to offline violence. To examine such mediation, explicit interactions are cumbersome to implement because there are five disinformation variables. Thus, a simple computational experiment was carried out instead by estimating the third model (excluding the regime change dummy variable) in subsamples divided by the median of the polarization variable.
The results from the sample split estimations are shown in Table 3. When looking at the coefficients and their signs, there indeed exist differences in terms of the disinformation variables. In the split full sample relatively large coefficient magnitudes are present in the low polarization regime within which governmental disinformation to domestic audiences and foreign government disinformation have coefficients with positive signs. The opposite holds in the high polarization regime. Thus, the results are still difficult to interpret for the full sample. In the EEC sample, however, the previously noted results seem to refer to countries in the high polarization regime. For these countries, disinformation disseminated to domestic audiences, whether by governments, political parties, or politicians, tends to increase the protest counts. All in all, it can be concluded that polarization indeed seems to mediate the effects of disinformation on protests, although this proxy effect is neither straightforward to model nor to interpret.

5 Conclusion

This paper evaluated the effect of online disinformation and other digital phenomena upon offline political protests in a time-series cross-sectional sample of 125 countries between 2000 and 2019. Based Bayesian multi-level regression analysis, the hypothesis contested holds; there is a statistical relation between disinformation and protests. However, in the full sample this relation only becomes visible once political polarization is taken into account; polarization itself has a strong tendency to increase protests no matter the sample used. In contrast, the results are clearer, aligning with prior expectations in the sample of EEC countries; disinformation propagated by both domestic and foreign governments tends to increase protests. Though, a proxy effect with political polarization seems to be again present; these effects apply particularly to countries experiencing high levels of polarization. While the hypothesis holds, the interpretation is not straightforward.

As for the other independent variables, a government’s capacity to shutdown the Internet has a notable negative effect upon the protest counts in the full sample of countries. This effect seems logical. If offline political protests are planned and coordinated online, as is claimed in the literature, shutting down the Internet obviously decreases protests. Although it could be reasoned that governmental social media monitoring would have a deterrence effect upon the planning and coordination activities, this line of reasoning does not hold. In fact, the absence of governmental monitoring of political content in social media seems to paradoxically decrease the offline protest counts. Furthermore, in the EEC sample a similar strong effect is absent. Also previous results have been rather mixed (Mercea 2011). In other words, online surveillance may either increase or decrease participation particularly in high-risk offline protests. More generally, according to Fuchs (2018), disinformation, hate speech, privacy, surveillance,

5 High polarization countries in the EEC sample include Poland, France, Germany, Italy, the Netherlands, Spain, Bulgaria, Croatia, Cyprus, Estonia, Finland, Greece, Luxembourg, Romania, Slovenia, and Hungary.
and related online phenomena also constitute one dimension that is shaping the current political activity on the traditional left-right axis.

A potential factor explaining the diverging results between the two samples is rooted in the so-called digital divide, which has long been used to describe societal aspects of information technology between developing and developed countries (Rogers 2001). There are no particular reasons to suspect that disinformation and its tenets would be different in this regard. Indeed, the mixed results can be interpreted also to reflect the existing Western and English language biases in disinformation research (Righetti 2021). A further point can be made about construct validity of some of the disinformation variables supplied in the V-Dem dataset.

Although information is always both outwardly and inwardly directed (Lin 2020), it is not entirely clear whether the separation between domestic and foreign audiences makes sense theoretically. Disinformation, like propaganda, is often designed for both audiences, and separating the two can be difficult (cf. Ruohonen 2021a). Nor is it clear how robust the protest dataset is for the paper’s purposes. Coding protests based on media articles is subject to known biases, among these the tendency of newspapers to only report long-lasting or otherwise major protests (Almeida 2019, pp. 37–42). In contrast—thanks to social media and the Internet’s overwhelming online advertising business, online disinformation may be targeted to highly specific groups who are susceptible to provocations seeking to prompt offline protests. Finally, as contemplated by Chang and Park (2020), a reverse causality may apply; people who participate in offline protests may turn online in order to continue their protesting. A similar reasoning may apply to disinformation dissemination.

In addition to patching these limitations, three paths seem important for further research. First, the mediation effects need further examination, but complex structural equation models are not necessarily the right tool for the task because also the longitudinal dimension needs to be accounted for. Second, further theoretical work is required to distinguish the state-centric viewpoint to disinformation from other viewpoints. The task is not easy, especially when considering that theoretical work in disinformation research has been extremely limited, mainly revolving around the terminological confusion. Finally, third, more policy-oriented research is required to gain practical relevance. As was noted in Section 3.3, numerous laws and other policy responses have already been enacted particularly in Europe. Research, however, lacks behind; there are not many studies that could reliably inform policy-making. The present paper is not an exception.

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Data Availability

The datasets used in this paper are publicly available online; please refer to Coppedge et al. (2021b,a), Clark and Regan (2016b), and World Bank (2021a,b).
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