The Influences of Misinformation on Incidences of Politically Motivated Violence in Europe

by

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TABLE OF CONTENTS

LIST OF TABLES v
LIST OF FIGURES vi
ABSTRACT vii

1 Introduction 1

2 Theoretical Motivation 4

3 Data 8

3.1 Time Series Plots 10
3.2 Temporally Collapsed Country Heat Maps 11
3.3 Testing Relationships 16
3.4 LASSO Regressions 19

4 Discussion and Conclusion 27

REFERENCES 31

A Additional Visualizations 36

LIST OF TABLES

Table 1: Small Lasso (Gaussian) Models of Political & Social Conflict in Europe 23

Table 2: Large Lasso (Gaussian) Models of Political & Social Conflict in Europe 25

LIST OF FIGURES

Figure 1: Time Series Plot of Misinformation Stories Across Europe 11

Figure 2: Temporally Collapsed Country Heat Map of Misinformation Intensity 13

Figure 3: Temporally Collapsed Country Heat Map of Civilian-Government Material Conflict 14

Figure 4: Temporally Collapsed Country Heat Map of Civilian-Civilian Material Conflict 16

Figure 5: Bivariate Relationship Between Misinformation & Civilian-Government Material Conflict, with GAM Trend Line 17

Figure 6: Bivariate Relationship Between Misinformation & Civilian-Government Verbal Conflict, with GAM Trend Line 17

Figure 7: Bivariate Relationship Between Misinformation & Civilian-Civilian Material Conflict, with GAM Trend Line 18

Figure 8: Bivariate Relationship Between Misinformation & Civilian-Civilian Verbal Conflict, with GAM Trend Line 18

Figure 9: Temporally Collapsed Country Heat Map of Civilian-Government Verbal Conflict 36

Figure 10: Temporally Collapsed Country Heat Map of Civilian-Civilian Verbal Conflict 37

ABSTRACT

In the modern era of social media and related forms of electronic media, the issue of misinformation has become increasingly prevalent. To this end, as recent US presidential elections and experiences in Ukraine in the lead-up to the 2022 Russian invasion each suggest, transnational misinformation in particular poses an increasing threat to the security and stability of modern nation states. Furthermore, at least anecdotally, there are claims of a direct relationship between misinformation narratives and domestic acts of politically motivated violence. Yet such claims lack systematic empirical evidence, especially as it relates to the global spread of misinformation by state-based or transnational actors. As these effects of transnational misinformation on domestic political unrest remain understudied, I collect and evaluate empirical evidence of such an association. My research more specifically assesses the effects of transnational misinformation on several distinct forms of domestic political violence within the context of Europe, sharpening our empirical understanding of the purported association between misinformation and political violence. This is achieved through the fusion of a fine grained spatial temporal dataset of confirmed instances of news-based misinformation with daily level event data on incidents of political conflict. These combined data are then modeled and analyzed using univariate and bivariate descriptive statistics and multivariate LASSO regression models of misinformation in Europe for the period covering January 2015 to May 2022. These analyses imply a positive association between misinformation and political violence in Europe for this time period. These findings additionally indicate

that this association is much stronger for civilian to government violence events than it is for civilian to civilian violence. Altogether this thesis accordingly provides novel empirical evidence for the pernicious effects of transnational misinformation on political violence.

Chapter 1

Introduction

Misinformation is now widely recognized as affecting many facets of modern life. Transnationally, we have seen a shift from misinformation's narrow targeting of electoral outcomes to influence campaigns oriented more broadly towards mass political behavior. Prominent examples of this include widespread misinformation casting doubts on the validity of the 2020 U.S. Presidential election or interfering in the 2019 Ukrainian Presidential election, putting forward messages ranging from the fraudulent use of mail in ballots to undermining the sovereignty of the nation (Ukraine Election Task Force, 2019; Mitchell, et al., 2021). In specific regard to misinformation as it pertains to politics or political events, misinformation's impact is potentially a contributing factor to political unrest via the incitement of disorder through heightened levels of uncertainty (Hook, 2022; Colomina, 2021). By merit of this dynamic, misinformation is conceivably capable of inciting domestic political unrest. Prime examples of this relationship include the January 6th insurrection, motivated by misinformation concerning the 2020 election, or increases in recorded hate crimes in the UK following Brexit, a referendum heavily impacted by misinformation campaigns (Sylwia, et al., 2021).

While the association of misinformation with political unrest may seem plausible given the increasingly large body of research linking misinformation to extremism and government distrust, and the anecdotes highlighted in the paragraph above, there is a deficiency in systematic empirical research on the linkages between misinformation and offline political violence (Muhammed, 2022; McCammon, 2021; Au, 2022). This deficit holds particularly true in regard to cross-national studies that allow one to better account and control for country-specific factors when evaluating the effects of misinformation on political violence. Moreover, while misinformation is understood to be impactful and relevant internationally, it is additionally notably increasing in prevalence in the pervasiveness by which it impacts everyday civilians' lives across the world. Each of these trends further raises the stakes for understanding the effects of misinformation on political violence.

Yet to study such dynamics in a systematic fashion, one must have data not only on misinformation across different country contexts and time, but also equally disaggregated data on societal reactions to it. The increasing availability of disaggregated political and social event data helps to address this latter concern (Schrodt, 2012; Beieler et al. 2017). That being said, such event data also remains underutilized in the study of social unrest, especially that concerning or resulting from misinformation. See for example, Hanna (2017), who points out that "the lack of high quality protest event data is a chronic issue in social movement research" (pg. 1). My research seeks to resolve this gap in a field that will likely continue to increase in relevance as the role of misinformation in domestic conflict and international relations continues to grow. Alongside the event data considered above, the scope of my research encompasses misinformation, which I define here as information that is incorrect regardless of the spreader's intent, rather than focusing on disinformation as it is difficult to consistently and reliably determine intent in the spread of a narrative.

More specifically, my thesis research addresses the relationship between misinformation and political conflict in Europe over the time range of 01/06/2015 through 05/17/2022. The decision to focus regionally on Europe was made due to data availability, and in recognition that Europe remains at the forefront of transnational targeting of misinformation (Pamment, 2020). The remainder of this thesis proceeds as follows. Beginning with an explanation of existing theory on the subject and current literature, I develop a series of empirical expectations concerning the effects of misinformation on political violence. Turning to my tests of these expectations, I then give context to, and present the data collected for, my thesis. This is followed by a presentation of the results relating transnational misinformation to political violence, which were obtained through various forms of descriptive data analysis and statistical modeling. I conclude with a discussion on the insights and implications that may be drawn from my analyses, including propositions for how future research could be improved, adapted, or inspired by said results.

Chapter 2

Theoretical Motivation

Following the rise of the internet and increasing prevalence of social media, the ability of misinformation to spread to wider populations has similarly grown. As stated previously, for the purposes of this study, misinformation is defined as information that is incorrect. Research suggests that misinformation, as defined here, poses a wide range of challenges to societies including to public health, trust in science, trust in the media, political polarization, democratic governance, radicalization and extremism, and potentially offline violence (Scheufele, 2019, Van der Linden, 2022, Anderson, 2017, Arayankalam, 2021). With regards to the political implications of misinformation, transnational misinformation – defined for the purposes of this study as misinformation that crosses national borders, either via source and recipient or recipient and subject – represents an especially notable challenge. Thus far research has suggested that transnational misinformation has the ability to undermine elections and democracy more generally (Sylwia, et al., 2021; McCammon, 2021; Au, 2022). In part as a result of these potential implications and others, many have now come to conclude that misinformation represents one of, if not the, biggest contemporary threats to developed democracies (Thompson 2022).

While transnational misinformation is relevant throughout the global community and its many developed democracies, it is of particular importance in Europe by merit of the region’s unique geographic and political composition. European nations are geographically very closely arranged, politically tending towards democratic governments. The majority of these nations are additionally politically and economically linked via the European Union. As a unit, the EU is a significant global participant, as are many European nations individually. These factors result in a region that is internationally highly impactful but by nature less cohesive than the institutions it supports should allow. Not only does this make Europe vulnerable to mis- or disinformation, it makes European nations a prime target for such activity (Pamment, 2020; Klepper, 2022). The best avenue to addressing the threat of misinformation begins with seeking to understand its effects and how they are inflicted.

Much of the literature pertaining to misinformation centers on examining its spread, identification, and addressment. However, research has also been recently conducted on the effects of social media-based misinformation or disinformation on offline violence. The work of James Piazza in his article “Fake News: the Effects of Social Media Disinformation on Domestic Terrorism” establishes that disinformation spread by political actors via social media leads to an increase in domestic terrorism through the enhancement of social political polarization. This research used a series of country-year (i.e., time-series cross-sectional) regression models to examine the effects of social media-based disinformation on domestic terrorism. Finding a degree of association in this respect, the study went on to establish that political polarization served as a key mediator for this relationship (Piazza 2022). By comparison, Ruohonen (2021) finds relatively more mixed results for the effects of disinformation on offline protests, and the partial mediating role of polarization in this process, in finding such patterns to be more compelling within a sample of European countries than for a (near) global sample. These findings notwithstanding, still others have implied caution in drawing direct causal conclusions between forms of online misinformation and offline violence given the challenges in measuring the former (Cinelli et al. 2021).

The above literature thereby implies that the effects of online misinformation on political and social violence, while probable, are not automatic or self-obvious. Rather, these effects are dependent upon the manner by which one measures misinformation, on the types of political violence considered, and on additional contextual factors (e.g., geography and/or politics). Importantly, research thus far has only considered a limited subset of variation in each of these latter respects. For example, the work finding linkages between misinformation and political violence that was summarized above has typically, and rather narrowly, considered only protest and domestic terrorism, as opposed to the full range of political violence.

Accordingly, the goal of the present research is to provide an extended empirical evaluation of the assertion that the spread of misinformation online has a degree of influence over the occurrence of politically motivated violence. In leveraging fine grained political event data, I will be able to consider the effects of misinformation on multiple forms of political violence that are distinct from heretofore examined terrorism actions and protests events in these contexts.[1] Importantly, political violence event data can be uniquely aggregated to the same fine grained temporal scales that misinformation accounts often exist in, thus allowing for the closest empirical tests possible of linkages between transnational misinformation and political violence. The use of political violence event data also enables me to better

[1] Political event data represent discrete records of ‘who did what to whom, where and when’ (Schrodt 2012; Norris et al. 2017; Bagozzi et al. 2021). Such data have been used in a wide variety of contexts for the study of political violence (Croicu, 2017; Hammond, Weidmann, 2014).

integrate the full range of violent outcomes with contextual and confounding factors related to geography, demographic, and politics. In these respects and others, I leverage previously unexplored sources and streams of misinformation in these contexts, so as to contribute new insights into the types of misinformation that may be more or less likely to cause violence.

The event data discussed above and below allows me to disaggregate and evaluate the effects of misinformation in relation to (i) the target of political violence (in my case, government versus civilian targets) and (ii) the level of political violence (in my case, separately considering verbal conflict and material conflict). My expectation prior to the execution of my research follows the intuitive conclusion that there would be a positive relationship between misinformation intensity and political violence of each form mentioned above. Drawing upon the literature reviewed above, the causal linkages – not explicitly tested below – underpinning this positive relationship relate to the potential for misinformation to radicalize and mobilize ordinary civilians against an intended (governmental or societal) target. I additionally hypothesize that this relationship will be similar in magnitude and reliability regardless of the type of conflict considered, and regardless of whether the violence identified is arising (i) between civilians or (ii) between civilians and their government. I now turn to describing the data that allows me to empirically evaluate these expectations.

Chapter 3

Data

The data used in this research was collected from multiple sources and was gathered, organized, and analyzed using Python and R. The two primary data sets—pertaining to my independent and dependent variables–consisted of misinformation incidence data and political violence event data. The misinformation incidence data for my independent variable was sourced from the EU-funded EUvsDisinfo database (EUvsDisinfo, https://euvsdisinfo.eu/). This data set identifies European country-directed false or distorted news articles and related media, the date on which the media originated, and the target countries of the misinformation, among other metadata. The temporal range of this data is from early January sixth of 2015 through May seventeenth of 2022. This data was acquired at the misinformation article-level, where each news article had a corresponding date and potentially multiple subject countries. The data was reformatted using Python to a country-day format to enable temporal and panel analyses. In this manner, the final misinformation variable used below corresponds to country-day counts of misinformation stories targeting each European country for the aforementioned time period.

The political violence event data used for my dependent variables was sourced from the US government-supported Integrated Crisis Early Warning System (ICEWS) event dataset (Boschee et al. 2015). ICEWS codes individual events sourced from multi-lingual news(wire) reports using natural language processing (NLP) and automated event coding, categorizing them into a variety of different event categories.

For the purpose of this study, the event categories pertaining to conflictive events are the primary focus, and these categories are collapsed into either verbal[2] or material[3] conflict event counts, in relation to particular actor pairings. These two forms of political violence aggregation have wide precedence in the literature (e.g., Bagozzi 2015, Chiba and Gleditsch 2017). The final event data counts for verbal and material conflict are then more specifically aggregated to the country-day level according to perpetrator-receiver pairs for European countries: government[4] to civilian[5], civilian to government, and civilian to civilian. Matching the previously stated temporal range for my misinformation variable, the final conflict event data variables used in this study data cover the period 01/06/2015 through 05/17/2022. Note that for most analyses below, these event counts are then logged via the natural log to address skewness and outliers after adding a value of 1 to all cases to avoid taking logs of zero count values.

The final variables described above, each organized in country-day format, were then analyzed individually and in relation to one another to evaluate the potential relationship between misinformation and the incidence of politically motivated violence within European countries. In what follows, I first provide descriptive plots

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[2] Corresponding to events coded to the following 2-digit CAMEO categories and every subcategory therein: Investigate, Demand, Disapprove, Reject, Threaten, and Reduce Relations.

[3] Corresponding to events coded to the following 2-digit CAMEO categories and every subcategory therein: Protest, Exhibit Force Posture, Coerce, Assault, Fight, and Use Unconventional Mass Violence.

[4] Government actors corresponded in any instance where a source or target's sector code(s) included one or more of the following entities: military, police, government, or more general references to the country as the actor.

[5] Civilian actors included any actor whose sector code(s) in ICEWS included one or more of the following sector code designations: general population, civilian, social, protestors, mobs, popular opposition, media, NGOs, or business.

of these individual variables over time and space. I then turn to a series of bivariate analyses that allow me to compare my misinformation-focused independent variable to each dependent variable measure of political violence. Following this, I turn to multivariate statistical analyses to further evaluate whether my bivariate findings hold after accounting for a wide variety of potential confounds.

3.1 Time Series Plots

As an initial descriptive representation of the data pertaining to my identified incidences of misinformation, a single collapsed time series was constructed and then plotted so as to enable readers to observe the variation and prevalence of misinformation stories in Europe within the time range of 01/06/2015 through 05/17/2022. Figure 1 presents this raw daily time series count of misinformation events across all European countries for the time period of interest in black. Since this daily time series is quite noisy, a smoothed trendline is additionally included in green, so as to better visualize the underlying trend in misinformation during this period. As can be seen in Figure 1, misinformation stories targeting European countries generally increase in number over the 2016-2022 period, albeit with some intermittent declines therein. Namely, the upward trend in misinformation stories overall is punctuated by a drop in such stories in early 2018 and again in 2022. Such declines may be worthy of investigation in their own right, though this is beyond the scope of the present study. Overall, we can conclude from these results that there exists ample variation in these data for my period of interest, and that the challenges of misinformation in Europe do appear to have increased during much of my temporal window of analysis.

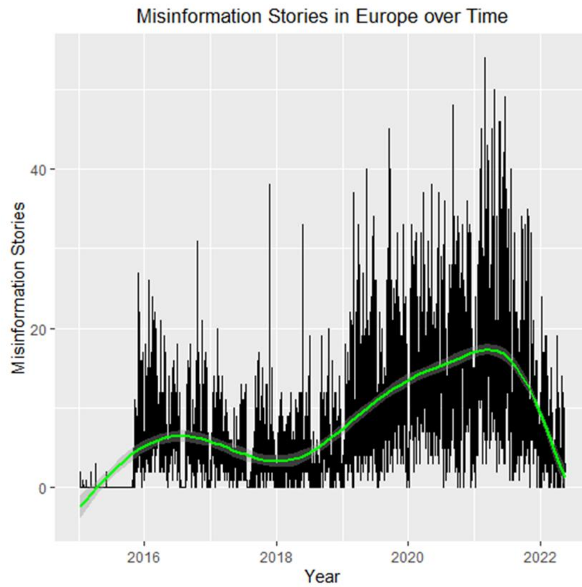

Figure 1: Time Series Plot of Misinformation Stories Across Europe

3.2 Temporally Collapsed Country Heat Maps

I now turn to providing descriptive evidence of my independent and dependent variables over geographic space. In the interest of conciseness, I primarily focus on (i) my misinformation independent variable and (ii) my material conflict dependent variables for these temporally collapsed maps. Similar maps for my verbal conflict dependent variables appear in the appendix and suggest comparable spatial patterns to those that I discuss for my material conflict measures below. In contrast to the time series plot presented above, all temporally collapsed country heat maps presented in Figures 2-4 below provide a richer picture of the spatial variation in misinformation and conflict as it relates to different European countries. A color scale, depicted on the right of each map, provides a visual intensity measure that ranges from low to high for the particular independent or dependent variable that appears in a given map. Each country in Europe for which there was data collected is then assigned a color according to the given scale.

The temporal collapse entails the summing of all instances of the given variable over the course of the entire data set, providing a single image depicting the conflict event, or news story, count of country-specific instances for a given variable over my full time period of analysis. Due to data skewness, examinations of plots using either logged or unlogged versions of each variable were considered. While the general findings and relationships were similar in each case, natural logged data are favored for these plots as it provided more interpretable results across a single relatively even scale. This is especially important given the uneven size, and hence total events and/or misinformation stories, that arise across different countries in Europe. Note that several of the ensuing analyses further below also make use of logged independent and/or dependent variable measures for similar reasons.

The Misinformation Intensity by Country map in Figure 2 illustrates the varying degree of misinformation incidences in Europe as distributed across countries. From this aggregation of my dependent variable, it can be determined that Russia and Ukraine experienced the highest intensity of misinformation targeting within the time range of 01/06/2015 through 05/17/2022. Poland, Belarus, Germany, France and the UK followed in terms of misinformation intensity within the same time period. By contrast, countries such as Iceland, Ireland, and Portugal saw relatively few instances of misinformation targeting during this same period. While these latter results may suggest that some variation in my misinformation measure is attributable to population size of particular European countries, I can note that the identification of Russia, Ukraine, Poland, Belarus, Germany, France, and the UK as countries experiencing higher rates of misinformation aligns relatively well with the countries typically highlighted as targets or dissemination of misinformation in Europe during this period.

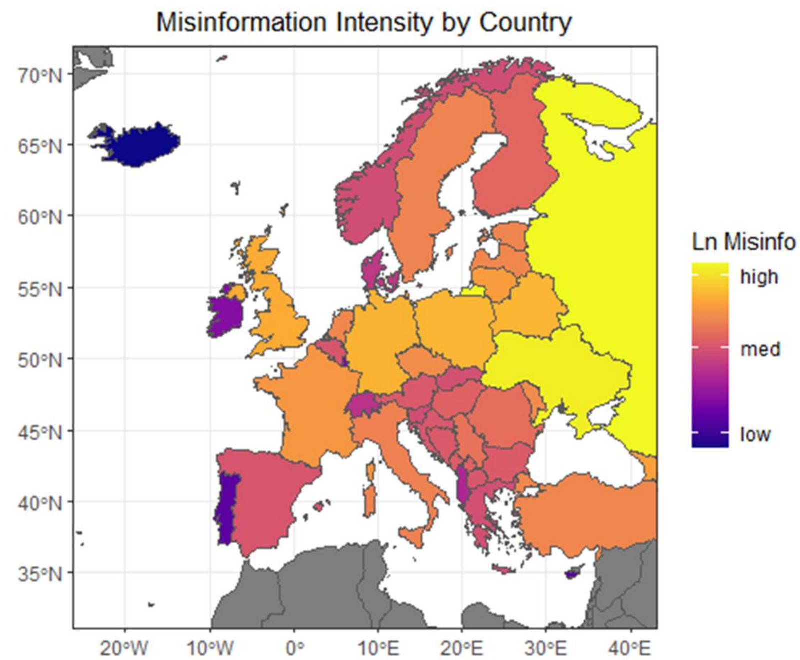

Figure 2: Temporally Collapsed Country Heat Map of Misinformation Intensity

In the Civilian-Government Material Conflict by Country map in Figure 3, Russia is again a clear outlier in regard to intensity of material conflict events. This is understandable as at least a share of my temporal sample encompasses a period where Russia was facing an insurgency within the North Caucasus, alongside lower forms of separatist unrest elsewhere. A number of other countries then suggest moderate levels of ‘material’ civilian-initiated political violence, namely Ukraine, the UK, France, and

Turkey. On the other hand, portions of Scandinavia and Central and Eastern Europe each reported relatively lower rates of this form of violence. Overall this map suggests that my material conflict dependent variable has a degree of face validity, thus providing confidence in my use of this measure within my ensuing bivariate and multivariate analyses.

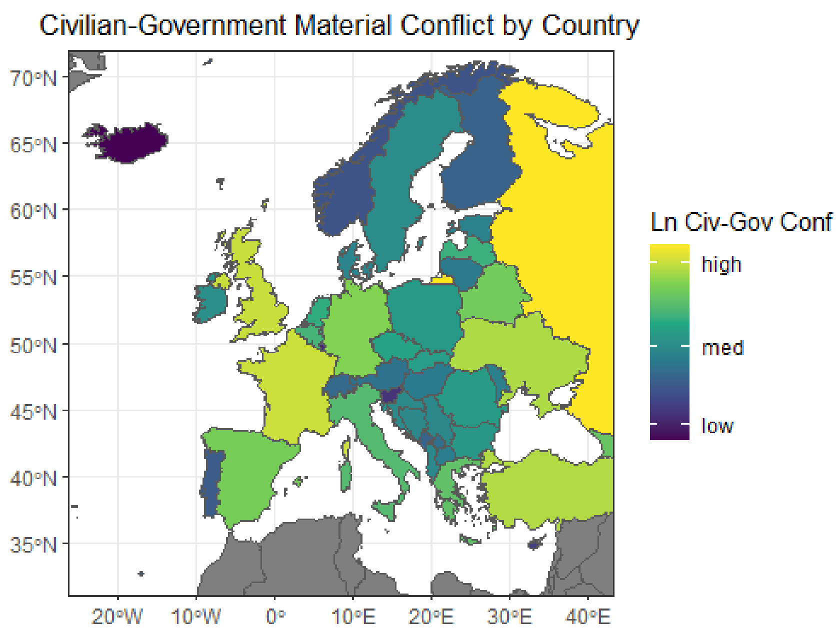

Figure 3: Temporally Collapsed Country Heat Map of Civilian-Government Material Conflict

The Civilian-Civilian Material Conflict by Country map appears in Figure 4. As can be seen in this Figure, this form of material conflict appears to be more broadly distributed in intensity across Europe than was the case in the previous map. This may be a function of there being more opportunities for civilian-to-civilian material conflicts within democracies across Europe, particularly in areas where tensions over economic challenges, and migration, are prevalent. Potentially confirming this contention, the UK, France, and Germany appear to exhibit high levels of civilian-civilian conflict that are nearly on par with Russia. Countries suggesting moderate levels of civilian-civilian conflict are Ukraine, Romania, and Turkey. By comparison, Iceland, Portugal, and Finland are examples of countries with low forms of this variant of violence. While some of these latter observations may again be a function of smaller population sizes, these results overall continue to exhibit a degree of face validity, while underscoring the rich variation in my political violence measures across space.

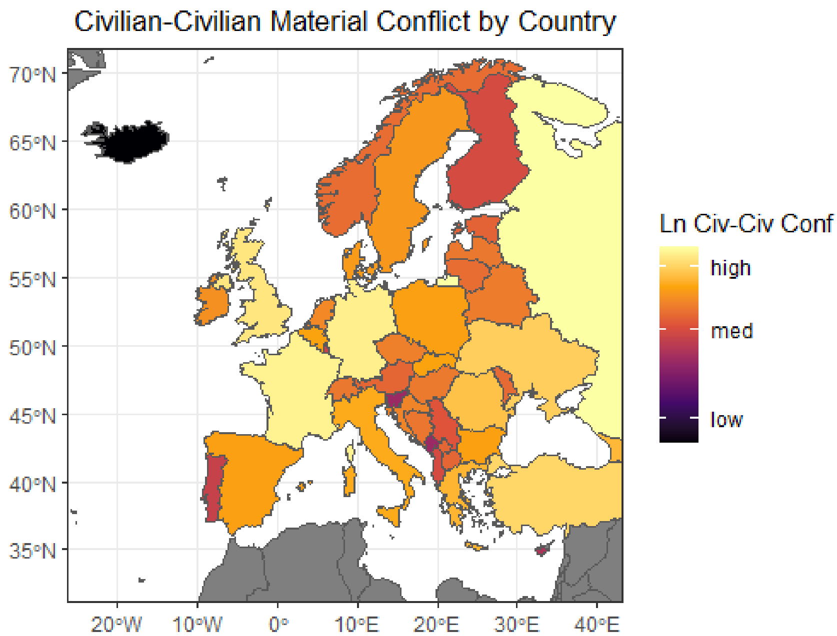

Figure 4: Temporally Collapsed Country Heat Map of Civilian-Civilian Material Conflict

3.3 Testing Relationships

Having established a degree of face validity, as well as spatial and temporal variation, in my aggregated dependent and (selected) independent variables above, I now turn to a series of direct bivariate comparisons between (i) misinformation and (ii) each form of intrastate political violence mentioned earlier. In contrast to the plots presented above, these comparisons return to my country-day-level measures of each relevant variable. These comparisons are additionally conducted via a series of bivariate plots that each compare the logged levels of misinformation (my independent variable, on each x-axis) to a logged measure of a given form of political violence (my dependent variables, on each y-axis). The plots appear in Figures 5-8, and illustrate the underlying relationship recovered in these instances via a generalized additive model (GAM)-smoothed trend line.

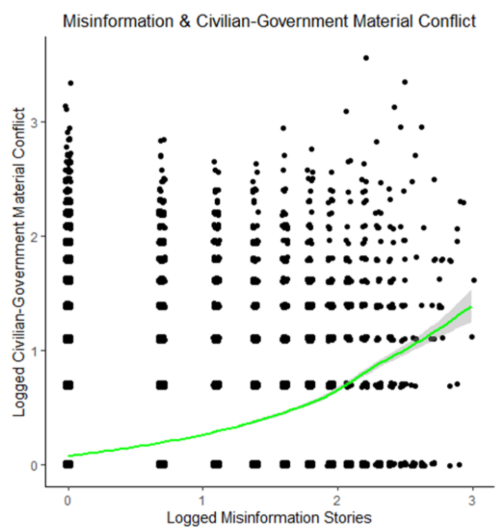

Figure 5: Bivariate Relationship Between Misinformation & Civilian-Government Material Conflict, with GAM Trend Line

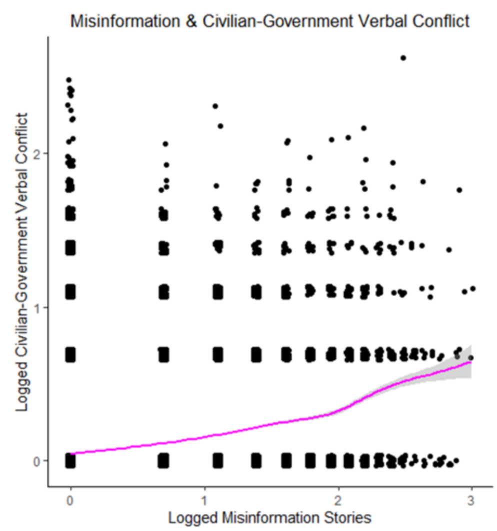

Figure 6: Bivariate Relationship Between Misinformation & Civilian-Government Verbal Conflict, with GAM Trend Line

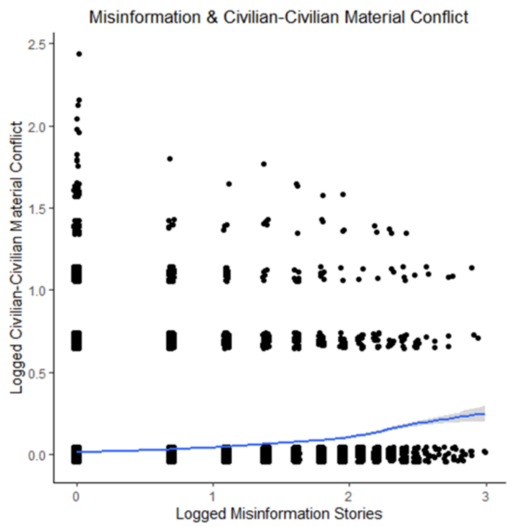

Figure 7: Bivariate Relationship Between Misinformation & Civilian-Civilian Material Conflict, with GAM Trend Line

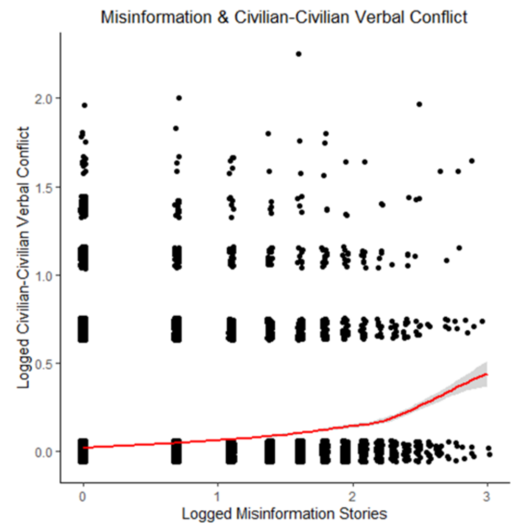

Figure 8: Bivariate Relationship Between Misinformation & Civilian-Civilian Verbal Conflict, with GAM Trend Line

These trend lines depicted in Figures 5-8 imply a positive association between misinformation and political violence in Europe for the time range of 2015-2022. That is, in each individual plot, one can observe that as the (logged) number of misinformation stories targeting a particular country increases, the corresponding rate of (logged) political violence within that same country also intensifies. These findings additionally indicate that this positive association is much stronger for civilian to government violence events (Figures 5-6) than it is for civilian to civilian violence (Figures 7-8), where the effect is fairly modest. These observations hold particularly true regarding material conflict, wherein the strength of association between misinformation and civilian to government material conflict appears stronger than that of the association between misinformation and civilian to government verbal conflict. Together, these bivariate findings provide suggestive evidence to indicate that increased rates of misinformation stories targeting particular European countries may lead to corresponding increases in the levels of intrastate political violence within those countries, particularly as it relates to violence initiated by civilians of those countries against those countries' governments. This helps to preliminarily confirm my overall expectation regarding the relationship between misinformation and political violence. At the same time, the variation in the strength of this association across (i) verbal and material conflict and (ii) civilian vs. government targets does not align with my earlier expectation that such misinformation effects will be consistent across these two dimensions.

The above findings and conclusions notwithstanding, it is also worth emphasizing that the bivariate plots examined here do not account for the potential that other omitted variables may be simultaneously driving the observed increases in both misinformation and political violence on these plots. To more rigorously evaluate my empirical expectations concerning misinformation and political violence, I thus need to reevaluate the relationship between misinformation and each form of political violence considered here whilst controlling for a variety of possible confounds. I do this in the following section in a LASSO-regression framework (Tibshirani, 1996), while still considering logged versions of my independent and dependent variables.

3.4 LASSO Regressions

A least absolute shrinkage and selection operator (LASSO) regression is an analysis method that allows for the estimation of the relationships between a dependent variable and one or more independent variables in a manner that is attentive to feature selection and regularization. The data structure for this analysis corresponds to panel data, measured at the country-day level for all European countries during the period 01/06/2015 through 05/17/2022. The regressions were run using the induced smoothed LASSO approach in R (Sottile et al. 2019), and the data used in the LASSO regressions is the same set as referenced in previous bivariate plots. The dependent variables considered in the regressions are logged versions of specific types of directed violence mentioned above, as measured via ICEWS (Boschee et al. 2015). Specifically, the four dependent variables considered are: *Ln Civ->Gov Material Conflict; Ln Civ->Gov Verbal Conflict; Ln Civ->Civ Material Conflict;* and *Ln Civ->Civ Verbal Conflict*. As above, these variables are logged in this case via the natural log in an effort to address severe skewness and significant outlier countries within the raw count-based measures of each form of conflict.

Given the logged nature of these dependent variables, the models considered below employ LASSO regressions with a Gaussian link function. The regression in this case allows for a penalized regression model framework, regularizing the coefficient estimates of some independent and control variables to zero in instances where they do not offer sufficient predictive power in the model. This provides for a higher quality analysis in relation to my hypothesis tests than would a standard regression model, as the independent and control variables that I consider below are now only retained as significant predictors if they exhibit substantial predictive power in relation to my dependent variables.

The main independent variable in this case is the natural log of the number of daily misinformation stories targeting a particular country on a given day, hereafter labeled *Ln Misinformation Counts*. Numerous control variables are then considered to account for possible country-year level confounding factors. These include the natural log of a country's annual population (*Ln Population*), the natural log of a country's GDP (*Ln GDP*), the percentage of a country's population that has access to the internet (*Internet Penetration*), and a country's *Military Expenditure* as a share of its GDP. All aforementioned control variables are taken from the World Bank's World Development Indicators (World Bank 2021). Additionally, indices corresponding to a country's levels of *Political Corruption and Electoral Democracy* are taken from the *Varieties of Democracy* project (Coppedge et al. 2021). To further control a country's international military influence, accounting for impact beyond its domestic levels of military expenditure, the number of annual *Military Alliances* held by a country is also included (Leeds et al. 2002). Finally, to better control for a country's baseline level of acute domestic conflict, a *Global Terrorism Index* (Institute for Economics and Peace 2020) is employed.

Several of the control variables mentioned above, including several that were sourced from the World Bank's World Development Indicators, are only available through 2019 or 2020. As a result, including these variables in my analyses drops the later years of my sample from my LASSO models due to listwise deletion. In light of this constraint, these particular control variables are hence entered into the models presented below in a staggered fashion, with a primary small specification followed by a larger robustness specification containing all aforementioned controls. This allows me to evaluate my anticipated relationships within a sample retaining a majority of my temporal sample (in the smaller model case) before re-evaluating these relationships within a smaller temporal range but while including additional control variables of interest for robustness (in the larger specification that I consider). While I put more weight on the primary smaller model specification in this case given the importance of capturing the post-2019 period in my analyses, I base my current conclusions on the findings that hold across each model specification.

Table 1, presented below, reports the results from a series of small model specifications for each of the four dependent variables outlined above (*Ln Civ->Gov Material Conflict; Ln Civ->Gov Verbal Conflict; Ln Civ->Civ Material Conflict*; and *Ln Civ->Civ Verbal Conflict*), when controlling for *Ln Population* and *Ln GDP*. Across each of these four model specifications, there is evidence to suggest that *Ln Misinformation Counts* exerts a statistically significant ($p<.01$) positive effect on the four respective measures of violence considered here. Holding constant a European country's levels of population and economic size, this implies that increases in the level of misinformation stories targeting a country are estimated to be associated with reliable increases in that country's observed levels of material and verbal conflict arising from civilians against the government as well as between civilians. From Table 1, the observation can be made that misinformation has the potential to spur increases in several forms of intra-state political and social violence. The control variables considered in Table 1 are also informative. For instance, *Ln Population* is statistically significant ($p<.01$) in all four model specifications. Controlling for misinformation and economic size, this implies that countries with overall higher populations are likely to see higher rates of each form of violence. That being said, *Ln GDP* is not statistically significant across a majority of the model specifications considered here. Where it is statistically significant ($p<.01$), it is negative. This suggests that larger economies in Europe are less likely to see high rates of material conflict between civilians and their governments, controlling for population and misinformation rates. Each of these control variable findings is intuitive.

Table 1: Small Lasso (Gaussian) Models of Political & Social Conflict in Europe

	Ln Civ->Gov Material Conflict	Ln Civ->Gov Verbal Conflict	Ln Civ->Civ Material Conflict	Ln Civ->Civ Verbal Conflict
Ln Misinformation Counts	0.105***	0.064***	0.008***	0.019***
	(0.004)	(0.003)	(0.002)	(0.002)
Ln Population	0.057***	0.025***	0.008***	0.011***
	(0.003)	(0.002)	(0.002)	(0.002)
Ln GDP	-0.011***	-0.000	0.003	0.003
	(0.003)	(0.002)	(0.002)	(0.002)
Intercept	-0.556***	-0.357***	-0.182***	-0.228***
	(0.019)	(0.014)	(0.008)	(0.009)
AIC	-13,566	-44,543	-140,917	-115,208
Lambda	7.064	20.923	7.147	9.803
N	85,293	85,293	85,293	85,293

Standard Errors in Parentheses; *** p<.01, **p<.05, *p<.10

For robustness, Table 2 presents the results from a set of four "large" model specifications considering each of the dependent variables mentioned earlier (*Ln Civ->Gov Material Conflict; Ln Civ->Gov Verbal Conflict; Ln Civ->Civ Material Conflict*; and *Ln Civ->Civ Verbal Conflict*). By virtue of these models being large specifications with additional controls, I am able to more confidently rule out the potentially confounding effects of my additional controls when assessing the relationship between misinformation and political violence. That being said, the findings from these larger specifications should be taken as relatively tentative, as the missingness on several controls during recent years requires me to omit several of my more recent years of data. This can be most readily seen via the change in total observations when moving from Table 1 (N=85,293) to Table 2 (N=53,507).

Across these four Table 2 specifications, Ln Misinformation Counts is no longer statistically significant in the large models considering *Ln Civ->Gov Material Conflict, Ln Civ->Civ Material Conflict*, and *Ln Civ->Civ Verbal Conflict*. However, *Ln Misinformation Counts* remains positive and statistically significant ($p<.01$) for the model considering *Ln Civ->Gov Verbal Conflict*. This indicates that increases in misinformation uniquely leads to reliably positive increases in verbal conflict initiated by civilians against their governments in Europe for the pre-2019 period, after controlling for population, economic development, internet penetration, military ties and resources, terrorism, democracy, and political corruption. However, null findings for the models considering *Ln Civ->Gov Material Conflict, Ln Civ->Civ Material Conflict,* and *Ln Civ->Civ Verbal Conflict* may not be decidedly attributable to the addition of the specific controls considered here. As noted above, these null findings may be attributable to the large loss in sample size that the addition of my large model specification's controls entails. Indeed, the sample sizes of the models in Table 2 is 53,507, which is significantly lower than the sample size of 85,293 in Table 1. This corresponds to the loss of any data from 2019 onward.

The control variables considered in Table 2 offer several additional insights. Holding all other factors in the model constant, electoral democracies are significantly ($p<.01$) more likely to see each form of violence considered here. The implication is then that democracies in the sample are more prone to conflict between civilians and between civilians and their government. This reflects the notion that holding all else constant, freer polities may enable civilians to partake in more forms of material and verbal conflict against their government and one another. Perhaps more intuitively, countries more highly ranked based upon the *Global Terrorism Index* consistently exhibit significantly (p<.01) higher levels of *Ln Civ->Gov Material Conflict*, *Ln Civ->Gov Verbal Conflict*, *Ln Civ->Civ Material Conflict*, and *Ln Civ->Civ Verbal Conflict*. None of the other control variables are statistically significant across all four models in Table 2. However, evidence from Table 2 does suggest that countries exhibiting higher levels of political corruption are significantly (p<.01) more likely to see increased levels of verbal conflict initiated by civilians against their government. More militarily active countries (measured via either *Military Alliances* or *Military Expenditure*) also appear to exhibit higher levels of civilian to government violence, all else remaining equal. *Ln GDP* appears to reliably (p<.01) *decrease Ln Civ->Gov Material Conflict*, but to also reliably (p<.01) increase *Ln Civ->Gov Verbal Conflict* and *Ln Civ->Civ Verbal Conflict*. *Internet Penetration* is not statistically significant in Table 2.

Table 2: Large Lasso (Gaussian) Models of Political & Social Conflict in Europe

	Ln Civ->Gov Material Conflict	Ln Civ->Gov Verbal Conflict	Ln Civ->Civ Material Conflict	Ln Civ->Civ Verbal Conflict
Ln Misinformation Counts	0.000	0.018***	-0.004	-0.002
	(0.002)	(0.004)	(0.003)	(0.003)
Ln Population	0.035***	-0.011**	0.004	0.000
	(0.007)	(0.005)	(0.003)	(0.001)
Ln GDP	-0.021***	0.018***	0.001	0.006***
	(0.006)	(0.004)	(0.003)	(0.002)
Internet Penetration	0.001	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Military Alliances	0.004**	0.003	0.001	0.001

	(0.002)	(0.002)	(0.002)	(0.001)
Electoral	0.061***	0.054***	0.015***	0.012***
Democracy	(0.012)	(0.009)	(0.005)	(0.004)
Political	-0.009	0.026***	-0.001	0.000
Corruption	(0.009)	(0.007)	(0.004)	(0.002)
Global Terrorism	0.032***	0.011***	0.006***	0.005***
Index	(0.002)	(0.002)	(0.002)	(0.001)
Military	0.013***	0.009***	0.001	0.003*
Expenditure	(0.002)	(0.002)	(0.002)	(0.002)
Intercept	-0.141***	-0.352***	-0.118***	-0.190***
	(0.045)	(0.033)	(0.019)	(0.013)
AIC	7,494	-25,244	-79,321	-68,690
Lambda	1.516	0.858	2.315	3.593
N	53,507	53,507	53,507	53,507

Chapter 4

Discussion and Conclusion

The analysis presented above highlights a number of key findings in regards to the relationship between misinformation and political conflict. First, misinformation stories targeting European countries have generally increased in frequency over the 01/06/2015 through 05/17/2022 period, supporting the widely held assumption that misinformation is regionally increasing in prevalence. Russia was a consistent outlier among European nations with high measurements of misinformation targeting intensity, Civilian-Government material conflict, and Civilian-Civilian material conflict. The UK and France additionally displayed moderate to high degrees of Civilian-Government material conflict, and Civilian-Civilian material conflict. Ukraine, while measuring high degrees of misinformation targeting intensity and Civilian-Government material conflict, exhibited comparatively lower levels of Civilian-Civilian material conflict. These findings are indicative of both the current misinformation environment in Europe as well as possible consequences of this environment for intrastate political and social conflict.

As a result of bivariate analyses, it was determined that there is evidence indicating that increased rates of misinformation stories targeting particular European countries may lead to corresponding increases in the levels of intrastate violence within those countries, particularly as it relates to violence initiated by civilians of those countries against those countries' governments. Upon the introduction of control variables to account for the possibility of omitted variables driving this identified relationship, the findings were further refined. Holding constant a European country's levels of population and economic size, LASSO regression analysis again indicated that increases in the level of misinformation stories targeting a country were associated with reliable increases in that country's observed levels of material and verbal conflict arising from civilians against the government as well as between civilians. This analysis, when repeated with an additional host of control variables, albeit with fewer observations due to the listwise deletion that these control variables' inclusion entailed, additionally indicated that increases in misinformation uniquely leads to reliably positive increases in verbal conflict initiated by civilians against their governments in Europe. This result came after controlling for population, economic development, internet penetration, military ties and resources, terrorism, democracy, and political corruption. For at least the 2016-2018 period, it can thus be concluded that verified misinformation exacerbates domestic civilian-to-government verbal violence, but that it may not exhibit similar effects on civilian-to-civilian (i.e. social) violence, nor on civilian-to-government material conflict.

The results summarized above align with my expectations that misinformation would result in an overall increase in political violence. However, my initial assumption that this effect would be similar in intensity across verbal and material conflict for both civilian and government targets was not supported, as demonstrated by the above analysis. The implications of these findings in regard to domestic, foreign, and international policy are numerous. Domestically, the influence of misinformation on civilian-to-government verbal conflict suggests that country specific misinformation is a contributing component to domestic unrest. Stringent monitoring of the spread and content of misinformation at the domestic level would therefore be necessary to inform counter-misinformation policy.

In regard to transnational misinformation, these findings confirm that investing in tracking misinformation through programs such as EUvsDisinfo is informative and worthwhile. While the current analysis was explanatory in nature, the results highlighted above suggest that similar modeling of the effects of EUvsDisinfo-derived misinformation on conflict event data may be useful for real time conflict forecasting and prediction. For either explanation or prediction, this thesis furthermore determines that attaining a coherent understanding of the (mis)information environment functionally aids in analyzing its impacts. This is applicable beyond domestic misinformation and is perhaps even more effective in application to larger country groupings, such as by geographic region. By framing misinformation incidences in relation to regional grouping, allowing for a broadened data set, a clearer understanding can be obtained of misinformation dynamics.

In considering future research, there are a number of avenues for improvement of the research conducted thus far and potential extensions of what has been completed. Future research should identify further or alternate controls that do not face the same constraints with regards to unavailable years of data as those presented above. That is, identifying control variables that are similar to those included in the large analysis above, but that do not exhibit problems of missingness, would allow one to more accurately assess whether the large model specification findings were the result of missingness versus the addition of these actual controls. An additional improvement would be to broaden the analysis of the data collected to incorporate the relations between the country mentions of the misinformation and the country targets of the misinformation. This could be visualized via network analysis, which could then additionally show a time lapse of misinformation activity, alongside the higher order dependencies in misinformation targeting. Adding this aspect to the current research would provide another dimension to the relational nature of misinformation and allow for conclusions to be drawn on the impacts of targeted misinformation or international relations on domestic conflict levels.

Additional extensions of this research would center on either expanding its scope or further developing the theoretical framework of understanding and analyzing misinformation. Expanding this research to include other geographic regions would allow for a broader event data selection and enable an examination of trends and relations on a larger scale than is possible working only with European countries. Additionally, this would allow for comparisons to be made between regions that could lead to interesting revelations regarding misinformation activity and impact in the broader global community. Further extensions of this research could center on modeling and analyzing the spread of misinformation from sources of origin across platforms such as twitter or other online outlets. Along a similar vein, another extension might be to focus on identifying misinformation distribution networks to better understand how misinformation is spread. No matter the case, the current research serves as a useful foundation for these and other extensions, in light of both the data and models developed, and the key empirical findings discussed above.

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Appendix

Additional Visualizations

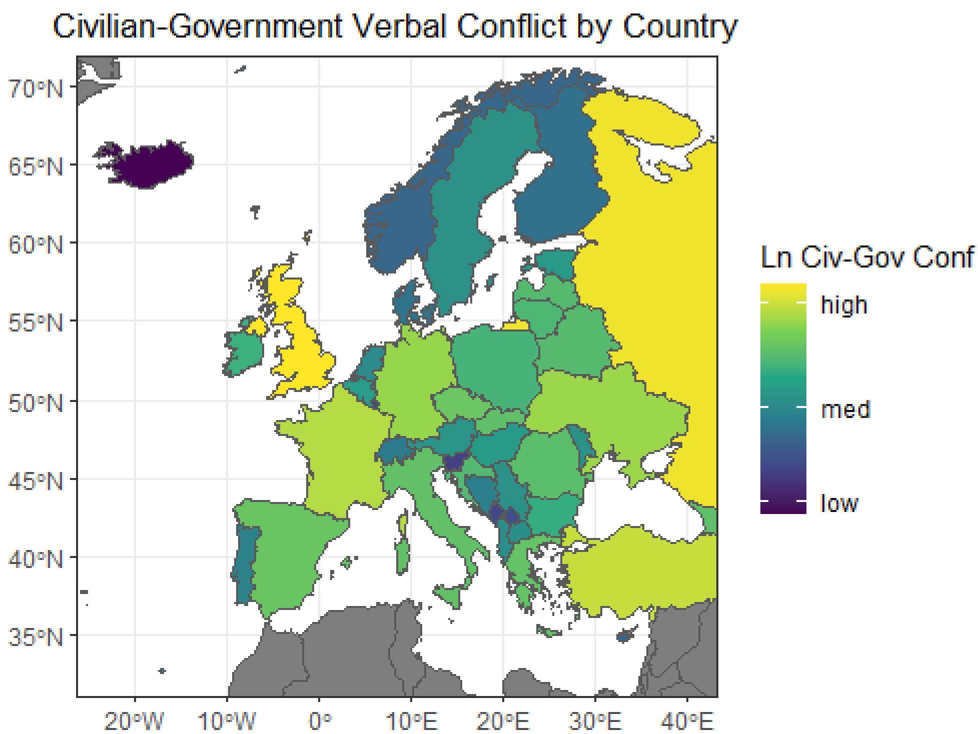

Figure 9: Temporally Collapsed Country Heat Map of Civilian-Government Verbal Conflict

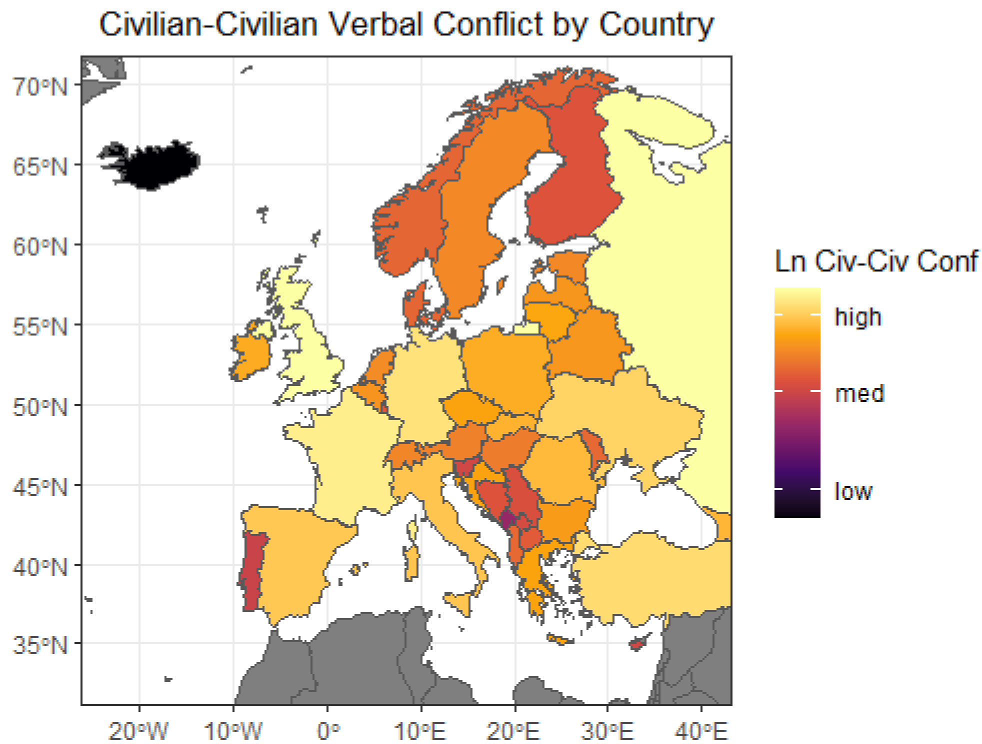

Figure 10: Temporally Collapsed Country Heat Map of Civilian-Civilian Verbal Conflict