From riot police to tweets: How world leaders use social media during contentious politics.*

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Abstract

How do leaders communicate in the midst of domestic instability and conflict? This question is central to their political survival. However, a comparative study of leaders' public rhetoric during contentious politics has proven elusive due to the difficulties of developing comparable measures across countries and over time. The advent of social media sites, and its widespread adoption by world leaders, offers a unique new source of data to overcome these challenges. Here, we use such data to examine two key explanations in the study of elite communication: the diversionary theory of foreign policy and the relationship between regime type and responsiveness to domestic publics. We test these hypotheses using a novel dataset that contains all social media posts (Facebook and Twitter) published by any head of state or government in all U.N.-member countries since 2012. We employ a combination of automated translation and supervised machine learning methods to characterize leader rhetoric along a series of key dimensions. Our findings show that leaders attempt to divert public attention during social unrest by emphasizing foreign policy issues, and that the greater degree of accountability associated with democratic institutions creates incentives for leaders to be more responsive to domestic audiences in democracies.

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1 Motivation

On September 25 and 26, 2018 Argentina's President, Mauricio Macri, sent out a series of tweets containing pictures and videos of meetings with various foreign dignitaries and a speech at the U.N. General Assembly (See Figure A1 in the Appendix.) While communications surrounding a president's foreign policy trip are not unusual, what is noteworthy is a topic that was not broached in President Macri's tweets. Namely, the widespread labor protests and 24-hour strike across Argentina in protest of I.M.F and Macri-backed austerity measures.[1] Why do leaders such as Macri choose to communicate and emphasize certain topics and not others? How does domestic unrest influence these decisions? What rhetorical styles do leaders employ when they communicate to their targeted audiences? These are crucial questions to scholars of comparative politics and international relations.

President Macri is not alone in his use of social media. U.S. President Donald Trump notably utilized Twitter throughout his presidential campaign, and has continued to do so while in office.[2] He solidified his hawkish rhetorical stance towards North Korea and its nascent nuclear missile program, warning that the US was "locked and loaded" in an August 11, 2017 tweet.[3] Indian Prime Minister Narendra Modi has been quite active on Twitter as well. With over 30 million followers, and popular Instagram and Facebook accounts, Modi has been credited as one of the most prolific and influential social media users.[4]

These examples are far from the exception. Leaders around the world use Twitter and Facebook to broadcast messages to both domestic and international audiences. Although the adoption of these platforms took place earlier in democratic countries, and in response to large episodes of social unrest such as the Arab Spring (Barberá and Zeitzoff, 2017), by now over 95% of governments have an active presence on social media sites.[5] This source of data has remained largely

[1]See "Argentina national strike protests inflation, shuts grains port", Reuters, September 25, 2018.

[2]See "Pithy, Mean and Powerful: How Donald Trump Mastered Twitter for 2016", The New York Times, October 5, 2018.

[3]See "Trump Says Military Is ?Locked and Loaded? and North Korea Will ?Regret? Threats", The New York Times, August 11, 2018.

[4]See "Megyn Kelly asked Narendra Modi if he uses Twitter. His 30 million followers responded.", The Washington Post, June 2, 2017.

[5]See Section 3.1

unexplored in the growing body of work studying how social networking sites are transforming democratic politics, which has focused its attention on dependent variables related to public opinion and mobilization. Previous work has examined how social media reflects salient foreign policy cleavages (Zeitzoff et al., 2015), domestic partisanship (Barberá, 2015), its effect on popular mobilization (Howard et al., 2011; Tufekci and Wilson, 2012; Barberá et al., 2015; Steinert-Threlkeld, 2017) and how leaders and government try to stymie protest and popular uprisings by engaging in censorship (King et al., 2013), or cutting Internet access during mass repression (Gohdes, 2015).

One may argue that the popular interest in how leaders use social media accounts is temporary, and ignited by the prolific use of Twitter by candidate – and now President – Donald Trump.[6] Yet the the use of social media sites by Trump and many other heads of state and government also highlights an important component of leadership that has been recognized by political theorists stretching back to Aristotle (Garver, 1994); namely, the impact of communication strategies, and in particular the rhetoric that leaders employ to communicate with their constituents and with other leaders (Conger, 1988; Krebs and Jackson, 2007; Mukunda, 2012; Pennebaker, 2013; Wedeen, 2015). Much of the extant work in political science on leaders has focused on institutional and biographical factors to explain leader behavior in office (Horowitz et al., 2015). A large literature has demonstrated that autocratic and democratic leaders differ in their willingness to invest in public goods (Olson, 1993; De Mesquita and Smith, 2011), to engage in repression to stifle dissent (Davenport, 2007), and to escalate conflicts (De Mesquita et al., 1999; Chiozza and Goemans, 2004).

In this paper we claim that data obtained from social media represents a new source of data that can advance our understanding of leader behavior. Much of the previous research on leaders communication has analyzed speeches and other public statements, and has been more qualitative in nature (Lasswell, 1948; Jagers and Walgrave, 2007; Krebs, 2015). Partly this is due to the difficulty of establishing valid cross-national measures of elite rhetoric that allow the comparison of leaders across countries and over time. The advent of social media, and its adoption by world leaders provides a common platform to examine variation in leaders' communication. We argue

[6]See "Commander-In-Tweet: Trump's Social Media Use And Presidential Media Avoidance", NPR, November 18, 2016.

that leaders are strategic in their public communication, and we now are able to measure those strategies from a comparative perspective through social media.

We argue that leaders make two key decisions regarding their communication tactics on social media: 1) how often to communicate with the public, and 2) which general policy area they want to discuss (domestic issues, foreign issues, non-political messages, etc.). Choices regarding these two dimensions provide important insights into understanding leader behavior. Our main set of hypotheses focuses on the effects of two contextual variables: domestic unrest (the level of public opposition that the leaders faces) and political institutions (democratic vs autocratic systems of government). We show that leaders respond strategically to the constraints of the context in which they are embedded. And even if we use social media data to test our hypotheses, we take their messages on Twitter and Facebook as a standardized representation of their overall communication strategies, which implies that our findings are generalizable to leaders' behavior, and not only on social media.

To our hypotheses, we use a novel dataset of all social media posts (Twitter and Facebook) by all world leaders that were active on at least one of these platforms as of August 2016. We rely on automated translation and machine learning methods to identify content related to domestic or foreign policy. Our results offer evidence in support of two key explanations of leader rhetoric. First, we find that leaders try to diverge their constituents' attention from domestic crises by emphasizing foreign policy issues. And second, we identify key differences in how autocratic and democratic leaders communicate: the latter tend to emphasize foreign policy; while the former appear to be more responsive to domestic publics and are more likely to employ diversionary rhetoric. These findings offer a unique new view into the factors that affect leaders' rhetoric and suggest new paths for future comparative research at the intersection of political communication and international relations.

2 Theory

2.1 The importance of elite rhetoric

How do leaders communicate during crises and unrests? What issues do they choose to emphasize, and how do they frame them? How do autocratic versus democratic leaders differ in their communication styles? And why does leader rhetoric matter? There is a broad literature in political science, communication, and leadership studies has explored how leaders use speeches and communication to frame issues and persuade audiences. We build on this past work as we develop our own hypotheses.

From US President Franklin Delano Roosevelt's famous radio fireside chats during World War II,[7] to the late Venezuelan President Hugo Chavez's use of a weekly television show to speak to his supporters, leaders have constantly tried to communicate with the public directly through different means. From the use and development of the semaphore telegraph during Napoleonic times to communicate during war,[8] to the booing of Romanian dictator Nicolae Causescu that emboldened protestors and led to his eventual ouster,[9] communication technology has been tightly coupled to conflict and leaders' own survival.

Part of leaders' appeal lies in their ability to motivate followers, set an agenda, and build a sustainable coalition (Van Vugt et al., 2008; Lakoff and Johnson, 2008). Leaders, particularly in democracies, constantly try to create narratives that can persuade voters (Krebs and Jackson, 2007; Krebs, 2015). There is limited evidence that charismatic leaders may be able to change people's minds on the basis of their words alone (Selb and Munzert, 2018). However, there is plenty of work demonstrating that elite rhetoric matters.

In the context of foreign policy, elites have the capacity to use rhetoric and cues to shape attitudes towards foreign policy (Berinsky, 2007; Baum and Potter, 2008; Krebs, 2015; Guisinger and

[7] See "How FDR?s Radio Voice Solved a Banking Crisis", TIME Maganize, March 12, 2015.

[8] See "How Napoleon's semaphore telegraph changed the world", BBC News, June 17, 2013.

[9] See Revolt in Rumania: Days of Death and Hope - A special report: How the Ceausescus Fell: Harnessing Popular Rage", The New York Times, January 7, 1990.

Saunders, 2017).[10] The choice of language that elites use can also influence other attitudes and behavior. For instance, Kalmoe (2014) finds that mild violent metaphors increase support for political violence, particularly among aggressive types, and they can further polarize the political discourse (Kalmoe et al., 2017). In more extreme examples, elite dehumanization of outgroups has found to increase support and actual participation in mass-killings and genocide (Yanagizawa-Drott, 2014), and long-term discriminatory beliefs (Voigtländer and Voth, 2015). Finally, there is further evidence that elite political incivility can serve as a signal for more general political intolerance (Nithyanand et al., 2017; Bursztyn et al., 2017; Siegel, 2018). Similarly, Weiss and Dafoe (2018) find in a survey experiment that Chinese respondents are sensitive to government aggressive rhetoric and exhibit a preference for blustery, nationalistic rhetoric.

Communication technologies play a key role in how elite rhetoric reaches the masses, and represent an important mechanism that can intensify the importance of elite messages. Social media platforms such as Twitter and Facebook represent perhaps the best example of technologies that have upended the traditional, top-down communication of past mass-communication channels (e.g., tv and radio). By allowing users to directly produce their own content, this affords new opportunities for mobilization, particularly in times of conflict. But leaders can also rely on these tools to instantly broadcast messages to the mass public. For instance, Turkish President Recep Tayyip Erdogan used FaceTime during a failed July 2016 coup to urge his followers out in the street to stop the coup plotters, with this request being circulated widely on social media.[11] The ensuing pro-Erdogan protests were seen as an integral factor in stopping the coup.[12] Governments have also used social media to reach international audiences during conflict, such as both Israel's and Hamas's extensive use of Twitter during the 2012 Gaza War to convince the international community of to the justness of their actions (Zeitzoff, 2016). Yet, social media is also a double edged sword for leaders. While providing a new platform to communicate with followers, it also allows new means for challengers and protestors to mobilize against the regime (Tucker et al., 2017). Many leaders and regimes have thus sought to assert control, or censor social media

[10] Others have also suggested that it is not just elites, but also social cues from peers that can change public opinion about foreign policy issues (Kertzer and Zeitzoff, 2017).

[11] See "Turkey rounds up plot suspects after thwarting coup against Erdogan", Reuters, July 15, 2016

[12] See "Erdogan Embraces Social Media to Repel Coup Attempt in U-Turn", The Wall Street Journal, July 17, 2016.

that challenges them (Morozov, 2012; Weidmann, 2015).

The goal of this paper is to shed some light on the mechanisms that explain how leaders decide to communicate with the public. To do so, we build upon two key explanations in the study of elite communication: the diversionary theory of war and the relationship between regime type and leaders' incentives to be responsive to domestic publics.

2.2 Diversionary rhetoric during contentious political times

The diversionary theory of war states that leaders who are facing domestic turmoil, and who do not have immediate solutions to pressing domestic problems, might attempt to divert the attention of the public away through the diversionary use of force (Sobek, 2007; Russett, 1990). Threatened by the domestic unrest, leaders seek to rally the public by initiating a foreign policy crisis or conflict abroad.

Diversionary uses of force can have a positive effect for the leader in two key ways. First, international conflict might simply divert the public's attention away from the issues that cause dissatisfaction. Second, a conflict with another country or international actors may rally support for the regime through an in-group/out-group psychological effect, meaning that a conflict with an out-group typically unites the members of the in-group (Simmel, 1955).[13]

A number of empirical studies provide support for this logic and show that leaders use diversionary tactics when facing low popularity and unrest at home. For example, Morgan and Anderson (1999) find that lower level of support for the prime minister's party in the U.K. are associated with an increased probability of the threat, display, or use of force. Similarly, Sprecher and DeRouen Jr (2002) show that Israeli political protests led to an increase in the use of force by Israel. Several cross-national studies also demonstrate that domestic economic decline positively relates with the probability of crisis escalation (Russett, 1990; James, 1988).

While the original version of the diversionary theory investigates motivations of leaders only

[13]Strong evidence in support of this "rally round the flag" logic is provided by the surge in presidential approval after the 9/11 attacks (see e.g. Kam and Ramos, 2008).

when they use force against the external other, a more recent, revised approach posits that leaders may sometimes resort to other distractions (short of the use of force) in order to divert the attention of the domestic public. Under such broader interpretation, leaders could use the threat of force or engage in other forms of escalatory discourse instead of engaging in an actual conflict (Hagan, 1986; Morgan and Bickers, 1992; Kanat, 2014). Instead of a costly and risky war, leaders might divert the attention of the domestic public by shifting the political discussion away from domestic problems to foreign policy. The power of escalatory rhetoric and aggressive foreign policy speeches has been demonstrated by scholars of public opinion, who show that rhetorical escalations might play an important role in increasing domestic support for the leader and uniting the people behind him (Marra et al., 1990; Brace and Hinckley, 1992).

Just as social media provides citizens new means to organize and try to hold politicians accountable, it also gives new tools for political leaders to try to shape public opinion. Recent research by King et al. (2013) and Roberts (2018) shows that Chinese leaders are quite responsive to (the threat of) collective action, and use various tactics such as censorship and distraction to stifle further unrest. Other research suggests that leaders may seek to distract or deemphasize poor news such as economic growth (Rozenas and Stukal, 2018), or 'flood' pro-protest social media information with irrelevant information to 'drown out' opposition voices (Munger et al., 2018) in so-called "astroturfing" strategies (Keller et al., 2017).

Based on this theoretical framework, we formulate the following two hypotheses:

H1: *During episodes of social unrest, leaders will attempt to divert the public's attention by increasing their overall social media activity.*

H2: *During episodes of social unrest, leaders will attempt to divert the public's attention from domestic issues by emphasizing foreign policy issues.*

These first two hypotheses are based on the idea that leaders seek to distract the public's attention away from the issues that cause dissatisfaction such as domestic unrest by trying to monopolize the political agenda with their own messages and by trying to shift the attention to foreign policy issues.

2.3 How political institutions affect leader rhetoric

Variation in how leaders use social media is likely to be related to institutional arrangements as well. Previous research has found that democratic leaders are quicker to adopt social media (Barberá and Zeitzoff, 2017). This result is consistent with the well-established finding that democratic leaders are forced to be more transparent, more responsive to constituents, and more willing to provide public goods because of the electoral connection (de Mesquita et al., 2005; De Mesquita et al., 2004; Cheibub et al., 2010). Conversely, leaders in autocracies are less willing to engage with constituents because they have alternative means to control social media and other channels of communication (Bueno de Mesquita and Downs, 2005; Gunitsky, 2015).

Institutions also shape the incentives for leader rhetoric. Previous research has found that autocratic leaders are principally occupied with staying power, and given their different institutional set-up compared to democratic leaders (Geddes et al., 2018). Other research by Weeks (2014) suggests that even within autocracies differential institutions face different constraints on their foreign policies.

Based on this previous research, we argue that institutions shape the differential electoral and institutional pressures and communication patterns of elites. Democratic leaders have a stronger incentive to communicate to a broader set of constituents, as compared to autocrats. While autocratic leaders have other tools to broadcast messages to the population – such as state-run media outlets – and to stifle dissent – such as harassment, arrests, and censorship (Way and Levitsky, 2006; Gunitsky, 2015) – democratic leaders have to rely more on the powers of persuasion given their dependence on electoral support for staying in power.

For these reasons, we expect to find differences in leaders' communication on social media depending on the type of political system. First, democratic leaders will be more active on social media. Second, their attention will be more closely attuned to domestic policy as these are crucial for their (re)election, whereas we would expect autocratic leaders to devote more attention to foreign policy issues, since the intended target of their messages will be more likely to be an international audience. In other words, we hypothesize that:

H3: *Democratic leaders will post more frequently on social media.*

H4: *Democratic leaders will be more likely to discuss domestic policy in their social media posts.*

Finally, democratic leaders will also be more likely to respond to social unrest, particularly before elections. Previous research on diversionary theory has indicated that diversion plays a bigger role in democratic polities (Gelpi, 1997; Miller, 1999). Democratic leaders, due to their vulnerability to domestic opposition and electoral concerns, are more likely to search for alternatives to distract public attention from domestic problems. While autocrats can often suppress opposition or control information so that citizens do not blame the government for poor domestic conditions, democratic leaders hold fewer options for dealing with unhappy publics (Clark et al. (2011), but see Kanat (2014) for a counterargument). Gelpi (1997) even goes so far as to call diversionary strategy a "pathology of democratic systems." Following this argument, we hypothesize that:

H5: *During episodes of social unrest, democratic leaders will utilize diversionary strategy more than autocratic leaders.*

3 Research design

3.1 Data: World Leaders on Social Media

To test our predictions, we build a new dataset that includes the social media accounts of the heads of state and heads of government of all 193 U.N. member countries. For each country, we identified a list of relevant names and institutions using the publicly available list from the United Nations Protocol and Liaison Service website (www.un.it/protocol) as of August 2016. For every name, we then manually searched the corresponding social media accounts (Twitter and Facebook), including both personal and institutional accounts.[14] When searching for accounts, we

[14]We consider as personal accounts those that prominently display the name of the world leader and use his or her image as profile picture. In contrast, institutional accounts clearly indicate that it is the office of the presidency or the prime minister office the one behind the social media account. For example, in the United Kingdom these Twitter accounts would correspond to @RoyalFamily for the head of state (with no personal account); and @theresa_may and @Number10gov for the head of government.

were careful to exclude parody or fake accounts. Our dataset partially builds on that collected by Barberá and Zeitzoff (2017), but it was revised and updated as of August 2016, and includes a broader set of social media accounts. Overall, we find that 184 out of 193 governments (95.3%) have at least one active social media account. Our dataset spans a total of 587 different accounts: 278 institutional accounts and 309 personal accounts.

The second step of the data collection process was to compile a dataset of all the social media communication that the leaders engaged in from January 1, 2012 to June 1, 2017 or during their tenure (if it started after or ended before these dates), which we captured through Twitter's REST API and Facebook's Graph API. The final outcome is a dataset of 285,414 Facebook posts and 609,224 tweets, which encompasses all social media communication of the world leaders for our period of analysis

A key challenge for our automated content analysis, which we describe in the following section, is that the social media posts in our dataset were written in 80 different languages. This makes it impractical to build different classifiers or dictionaries to classify posts in all different languages. To avoid this problem, we follow the set of recommendations outlined by Lucas et al. (2015) and De Vries et al. (2018), who show that machine translation to a single "bridge" language makes it possible to apply automated text analysis methods to documents in multiple languages. For that reason, we translate all non-English social media posts in our dataset to English, the most common language in our dataset (36.7% of tweets and 17.4% of Facebook posts are written in English). To facilitate language identification, we pre-process the data by removing urls, Twitter handles, and emojis from all posts. We then use the Google Translate API through the Google API client library for Python to predict the language, and translate all the posts in our dataset into English. For the time period under investigation posts on Twitter had a character limit of 140 character. Facebook posts, the other hand, have a character limit of 63,206 characters, which is roughly three times the length of the US constitution.[15] To ensure that the classification of topic is accurate while keeping translation costs manageable, we truncate Facebook posts at 1,000 characters.[16]

[15]See https://mashable.com/2012/01/04/facebook-character-limit/#LM10Rf_9Zaqr

[16]This only affects 13.9% of the Facebook posts. We truncate the rest of the text because the remaining words are likely to be related to the same subject as the first part of the post.

To ensure that the automated translation is not affecting our main results, we recorded whether the account posting the messages generally writes in English or in the native language of the country, and use it as a control variable in our analysis. We also graded the translations of a random sample of translated posts (220 Tweets, and 220 Facebook posts) through human review, by comparing both the original and the translated post with each other and assessing the accuracy of content and tone. We find that virtually in all cases the general meaning of the post remains the same.

3.2 Methods

Given the size of the dataset containing all social media posts by world leaders, we rely on automated text analysis methods to measure content type (domestic or foreign policy). We will then combine this dataset with a set of additional independent variables that measure the degree of social unrest, institutional characteristics, and level of development. We now offer more details on how each of these variables was measured.

3.2.1 Attention to Domestic vs Foreign Policy

We rely on supervised machine learning methods to measure attention to domestic vs foreign policy. This technique, originally developed by computer scientists (Hastie et al., 2009), takes a corpus of documents manually classified by humans into different categories (*training dataset*) to then *learn* the specific features of each text source that better predict their association to the each class. For example, if we want to identify documents about domestic policy issues vs foreign policy issues, we may find that words like "election", "health" or "education" tend to appear more among the first group, whereas words like "diplomatic", "treaty" or "visit" may appear more frequently among the second. Then we would use this information to predict whether new documents (not labeled by human coders, the *test dataset*) belong to one category or the other. For applications of machine learning to political science, see e.g. Grimmer et al. (2014); Barberá et al. (2016); Theocharis et al. (2016).

Our training dataset was put together with the help of undergraduate students at two of the authors' institutions. We manually labeled a random sample (stratified by country, account type, and platform) of 4,749 unique social media posts and a total of 6,000 codings (which includes posts that were coded multiple times to assess intercoder reliability). The coding scheme included four main categories: domestic policy, foreign policy, personal updates, and others/news. In cases when several of these categories appeared in the post, we asked our coders to try to capture the *key* content of the post. We obtained an average pairwise agreement between coders (computed on a random sample of posts labeled by multiple coders) of 90%. This indicates that our categories are sufficiently specific and exhaustive.

The process to automatically classify social media posts is divided in three different steps. First, we apply standard text pre-processing techniques to both our (translated) training and test datasets: convert to lowercase, remove stopwords, digits, punctuation and URLs, and split into unigrams (single words) and bigrams (sets of two words). We kept all hashtags as they were published, but substituted Twitter usernames with just an @ sign to avoid overfitting (Theocharis et al., 2016). To remove extremely rare expressions that are likely to contain little information, we only kept unigrams and bigrams that appear in two or more documents. After these pre-processing steps, our training dataset is reduced to a document-feature matrix that contains 4,204 social media posts (in the rows) and 37,455 unique n-grams (in the columns).

The second step is to train our multinomial classifier; that is, to estimate what features better predict our four categories of interest. We use *xgboost* (Chen and Guestrin, 2016), a state-of-the-art machine classification method that relies on gradient boosting (an ensemble of decision trees), and which has been recently found to maximize classification accuracy in most tasks (Olson et al., 2017). The intuition for this method is as follows: the classifier tries to partition the documents in the dataset multiple times and into multiple groups based on whether they mention or not specific combinations of n-grams, and the goal is to find the specific partition that maximizes the proportion of documents that are classified correctly. We train this classifier using 5-fold cross-validation to identify the parameters that maximize in-sample performance, and then measure how well it performs on a random 20% of the training dataset that was left out of the estimation.

Table 1: Out-of-sample performance of machine learning classifiers

Variable	Accuracy	Precision	Recall	Baseline
Domestic policy	0.722	0.654	0.633	38.8%
Foreign policy	0.782	0.671	0.644	31.2%
Personal	0.914	0.265	0.162	4.1%
Others	0.757	0.443	0.551	26.5%

Notes: *accuracy* is the % of social media posts correctly classified; *precision* is the % of posts predicted to be in that category that are correctly classified; *recall* is the % of posts in that category that are correctly classified; *baseline* is the proportion of posts in that category.

Table 1 reports the out-of-sample performance of this classifier. The results show that we are able to distinguish with confidence between domestic and foreign policy, but also that personal content is more difficult to identify. Considering that we have four categories and that our main dimension of interest (domestic vs foreign policy) is accurately capture, we claim that this level of performance is sufficient to continue with our analysis. Any potential prediction error would contribute to the overall level of measurement error in our models and lead to attenuation bias, which would mean our estimates are conservative.[17]

Another way to evaluate the performance of our classifiers is to estimate the n-grams with the highest *feature importance*, that is, those that more clearly segment the data into categories. Table 2 shows the list of words (up to 25 per category) with highest feature importance, weighted by frequency. Among the words that best predict domestic policy we find "government", "national", "health", "employment", "education"; whereas among the equivalent words for foreign policy we see "foreign", "fm" (foreign minister), "meeting", "countries", "cooperation", "visit", "relations", "ambassador", etc. We take this to be strong evidence that we are indeed capturing our latent construct of interest – the policy area to which the social media post refers.

The third and final step in our analysis is to use our classifier to predict the probability that each individual tweet and Facebook post in our dataset refers to domestic or foreign policy issues. In our analysis, we will aggregate these quantities at the account-month level, which will also help alleviate any concerns about measurement bias. Table C3 in the Appendix offers descriptive statis-

[17]See Tables B1 and B2 for performance of the classifiers split by language and source (Twitter vs Facebook). We find that our classifiers perform equally well in English and in other languages, which confirms the validity of our machine translation approach. As expected given their shorter length, tweets are somewhat more difficult to classify automatically, although the overall performance levels are still satisfactory.

Table 2: n-grams with highest feature importance for each category

Content type classifier	
Domestic	of_the, to_the, government, national, education, approved, employment, school, health, of_our, knowledge, thanks, project, year, public, for_the, construction, celebrate, 2011, increase, civil, tune, arrival, social, the_national, do_not, society, system, young, billion, in_the, ministry_of, will_be, students, enjoy, chance, work, research, economy
Foreign	foreign, fm, meeting, countries, cooperation, visit, summit, relations, ambassador, meets, the_united, forum, china, eu, president, un, terrorism, turkey, the_european, geneva, met_with, nations, minister, condolences, bilateral, europe, consulate, cuba, ecuadorian, receives, press, relationship, attack, to_attend, embassy, partners, africa, delegation, poland, human, states
Personal	happy, wishes, book, thoughts, birthday, lhl, you_very, holiday, vanuatu, has_never, you_going, 2016, agreement_august, for_your, poem, always_remember, his_life, interesting, mount, missed, always_in, scholarships, malta, #newcare, nationality, busy_day, ny, condolances, my_deepest, rep, deepest_condolences, happy_king, apply, can_start

tics for the number of posts per account and month, as well as the proportion of posts classified into each of our two main categories.

3.2.2 Measuring Social Unrest

We measure social unrest by constructing a month-level index of social unrest for every country in our sample. Social unrest is coded using data from the International Crisis Early Warning System (ICEWS) Project. ICEWS is a project maintained by Defense Advanced Research Projects Agency (DARPA) grant and is intended as an early-warning system for the US military (see O'brien 2010; Metternich et al. 2013; D'Orazio and Yonamine 2015). The data collected through the ICEWS project includes several million daily events that are coded from a range of news sources, using a 'who did what to whom' structure. As a result, each event identifies a source actor, an event type (using the CAMEO codebook developed by Schrodt (2012)), and a target actor.

We define social unrest as the log count of *hostile* events of domestic non-state actors directed against the government. Non-state actors include protestors, opposition groups, civilians, social groups, dissidents, as well as rebels. We include events that fall under the CAMEO event codes: *make public statement*, *appeal*, *disapprove*, *reject*, *threaten*, *protest*, *assault*, and *fight*. Government actors include: *government*, *military*, *policy*, *legislative*, *judicial, and elite*.[18]

To help us disentangle the effect of social unrest on leaders' rhetoric, we further refine our measure of social unrest into two subcomponents depending on the type of event. Our first metric is low-level unrest, and correspond to making public statements or appeals, and to disapprove or reject a statement by the government. Our second component is high-level unrest, and consists on events in which actors threaten or protest, or when the use coercion, assault or fight. The sum of both components is our overall metric of social unrest.

3.2.3 Additional Independent Variables

Our theoretical argument assumes that governments (in democracies) are likely to be more responsive in the context of elections. We collect data on all presidential and legislative election dates from the IFES ElectionGuide[19], and include the number of days until the next election (logged) to measure whether responsiveness increases as elections draw close. We also include an term that interacts *days until election (logged)* with our *social unrest* measure, to account for increased responsiveness in the context of social unrest prior to elections.

We use the revised Polity IV scores (Marshall et al., 2017) to classify countries as either autocratic, semi-autocratic, semi-democratic, or democratic.[20] We interact our regime type measure with our *social unrest* indicator to account for different levels of responsiveness during social unrest in different institutional settings.

To measure economic and population development, we include year-level World Bank data on GDP per capita and GDP growth, as well as population size. We also include the percentage of

[18] It is important to note that because ICEWS is a project maintained for US military purposes, the data do not include events that took place in the United States, which means that in our analysis the event count for the U.S. is zero. In Appendix A we replicate all our analysis excluding the U.S., finding almost identical results.

[19] See http://www.electionguide.org/

[20] We use the conventional cut-offs for Polity2, whereby: (autocracy: -10:-8), (semi-autocracy: -7:0), (semi-democracy: 1-7), (democracy: 8-10).

population with Internet access from the International Telecommunication Union (ITU); which we predict for 2017 using linear interpolation. Finally, we also include region-fixed effects to account for possible unobserved heterogeneity. Table C3 in the Appendix describes all our variables.

4 Results

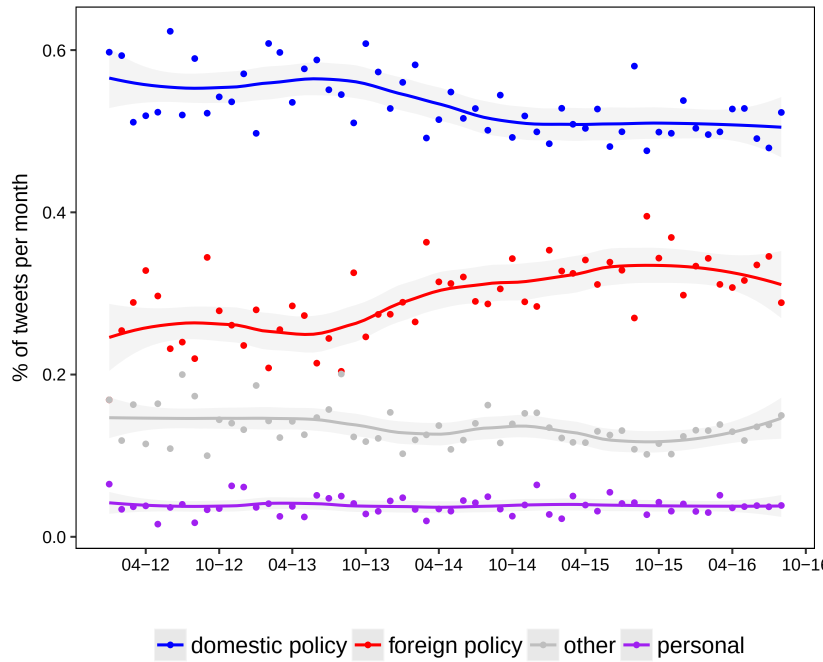
4.1 Descriptive Results

To get a first idea of the distribution of issues addressed in social media posts, we plot the monthly proportion of tweets by topic area from 2012 to August 2016.[21] Overall, the majority of topics discussed by world leaders on social media are concerned with domestic issues. Almost half of all social media posts in our dataset (49%) are related to domestic policy, whereas only 28% focuses on foreign policy. Over time, the proportion of foreign policy content does increase, thereby slightly reducing the gap between domestic and foreign policy content. Note that this could be due to a change in which countries are included in our sample, given that autocracies (more likely to post about foreign policy, as we will show next) generally adopted social media somewhat later. Other content fills up just below 20% of all social media posts, and personal posts only make a very small minority of leaders' social media communication.

Figure 2 shows how much of their time on social media world leaders spend talking about domestic issues. The world map reveals that leaders in different countries have quite different priorities in terms of their social media communication. Leaders in South America, the US, Spain, South Africa, and parts of Southeast Asia spend well over half of their time talking about domestic issues on social media. In large parts of Europe and Asia, and Africa domestic issues have a less important role in social media communication. In a select number of countries, social media is hardly used for domestic purposes at all, including Canada or Germany. Leaders seem to primarily use Twitter and Facebook for foreign policy in these countries. Finally, the map shows the countries where leaders have no official Twitter or Facebook accounts. These include China,

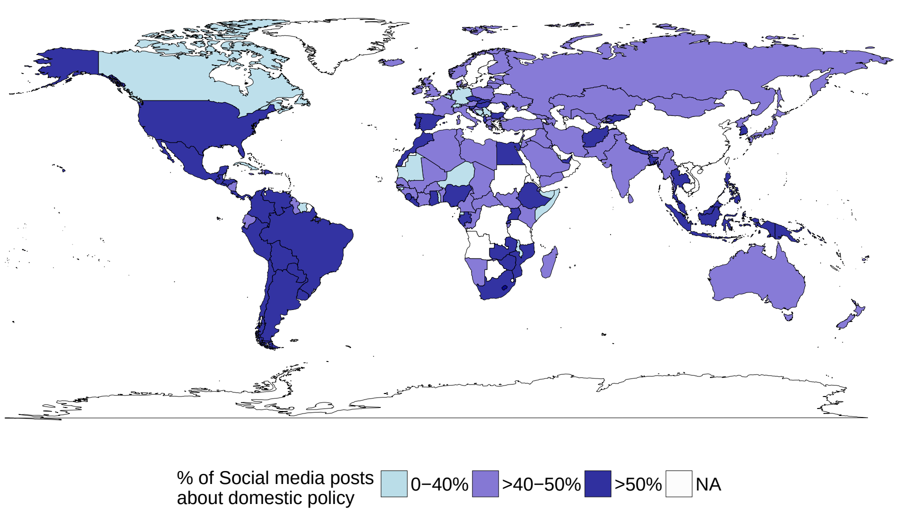
[21] We plot the actual monthly proportions as points and include the smoothed conditional mean using a LOESS function.

Figure 1: Monthly tweets (%)



Myanmar, large parts of Central Africa, as well as Turkmenistan and Uzbekistan.

Figure 2: % of Tweets that deal with domestic issues



4.2 Predictors of social media activity

As a first step in our empirical analysis, we examine the factors that predict world leaders' level of social media activity, measured as the logged number of social media posts (in each platform) at the month level for each account. Table 3 displays the coefficients estimates for a set of multivariate regressions of social media activity on each of our main covariates of interest. Each column shows results for a different model specification or subsample of our dataset: the full sample, including social unrest measured as low-level actions or high-level actions, only Twitter, only Facebook, and only democracies.

Table 3: OLS regression of monthly social media post counts by account

	Full sample (1)	Low level (2)	High level (3)	Twitter (4)	Facebook (5)	Polity > 0 (6)
Twitter (0-1)	0.31***	0.31***	0.31***			0.03
	(0.02)	(0.02)	(0.02)			(0.05)
Personal account (0-1)	−0.55***	−0.55***	−0.54***	−0.61***	−0.47***	−0.66***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Head of State (0-1)	−0.002	−0.0001	−0.01	−0.03	−0.002	−0.02
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)
Own language (0-1)	0.31***	0.30***	0.30***	0.33***		0.60***
	(0.03)	(0.03)	(0.03)	(0.03)		(0.07)
Unrest (log event count)	0.09***			0.08***	0.12***	0.22***
	(0.01)			(0.01)	(0.01)	(0.08)
Unrest (low-level only)		0.09***				
		(0.01)				
Unrest (high-level only)			0.10***			
			(0.01)			
Democracy (0-1)	−0.13***	−0.13***	−0.13***	−0.08***	−0.27***	−0.79***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.07)
Days until election (log)						0.01
						(0.04)
Unrest x Days til elec.						−0.03**
						(0.01)
Constant	1.66***	1.60***	1.58***	1.56***	2.66***	3.87***
	(0.24)	(0.24)	(0.23)	(0.33)	(0.34)	(0.62)
N	14,615	14,615	14,615	8,618	5,997	2,805
Adjusted R^2	0.16	0.16	0.16	0.17	0.15	0.20
Residual Std. Error	1.13	1.13	1.13	1.17	1.05	1.07

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$. Controls (omitted from regression): GDP per capita, GDP growth, internet access, log population size, year and region fixed effects.

We find that leaders tend to be around 35% more active on Twitter than on Facebook. This result is consistent with the descriptive statistics in Table C3: the average leader shares around 25 posts on Facebook per month, and sends 35 tweets per month. The type of account also matters: institutional accounts tend to be more active than personal accounts and accounts sharing messages on the country's native language post more frequently. We don't find any significant differences between accounts that belong to a head of state and accounts that belong to a head of government.

Table 3 also offers evidence in support of Hypothesis 1, regarding the diversionary tactics that leaders can employ. We find that levels of social media activity increase during periods of higher social unrest. A one-unit increase in our measure of unrest (i.e. a 100% increase) is associated with an increase in the number of social media posts of around 10%. To put this finding into perspective, note that the model predicts that the leader of a country such as Poland, with an average of 10 social unrest events per month in 2016, would increase the number of social media posts it shares each month from 29 to 38 (+30%), if the levels of social unrest were to increase to those in a country such as Ukraine, where the average number of unrest events were 33 during the same period. This finding is robust regardless of whether we look at low-level or high-level types of unrest and whether we focus only on Twitter or only on Facebook.[22]

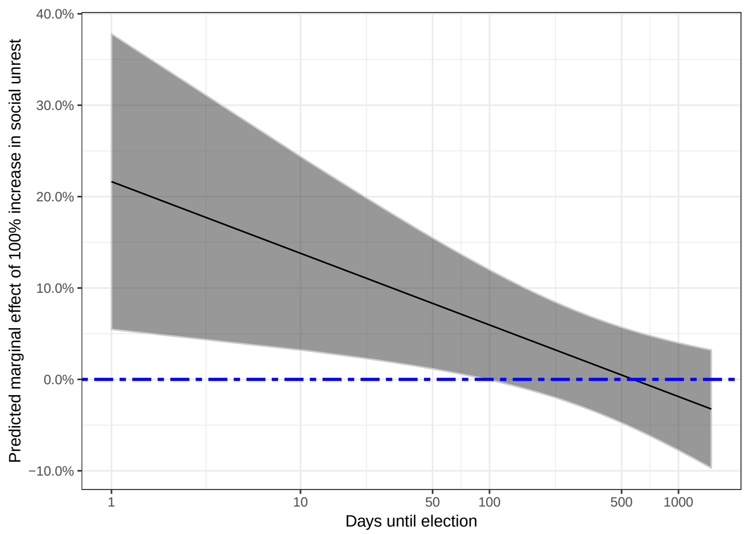
Contrary to our expectation in Hypothesis 3, however, we find that autocratic leaders tend to be more active: holding other variables constant, democratic leaders tend to post 13% fewer posts per month than autocratic leaders. This difference is larger on Facebook than on Twitter.

As a first exploration of Hypothesis 5, we also examine whether the magnitude of the effect of social unrest on social media activity varies as a function of proximity to the election (only for countries that hold competitive elections). If our hypothesis is correct, we should observe a larger effect when the number of days until the next election is low. The last column of Table 3 allows us to observe if that's the case, by estimating a model that includes an interaction effect between our measure of social unrest and the proximity to an election, measured in (logged) days. The negative sign for the coefficient of the interaction offers support for our hypothesis. To facilitate the interpretation of this result, we also show a marginal effect plot on Figure 3. Our results show that the level of social media activity is predicted to increase in around 20% after a one-

[22] In Table D4 in the Appendix we also show that the effect of social unrest appears to be curvilinear: it increases in magnitude for large-scale social unrest events, as evidenced by the positive sign of the coefficient when we square it. When we disaggregate unrest into four smaller event types, we also find that the magnitude increases for unrest that involves violence. In Table D5 we also show that the effect of social unrest on count of social media posts in autocracies is only statistically significant in military regimes.

unit increase in social unrest if such change happens within the last month before an election. However, if the election is more than 100-200 days away, the effect becomes virtually zero.

Figure 3: Marginal effect of social unrest on number of social media posts by month



4.3 Predictors of rhetoric style

Table 4 presents our main results regarding attention to domestic vs foreign policy issues. Here, the sample is the same across columns, but the dependent variable changes: the proportion of posts related to domestic policy in Column 1, and the proportion related to foreign policy in Columns 2–4. As earlier, we find differences across platforms and account types: there is less discussion of foreign and (especially) domestic policy on Twitter, which means it is considered a place to share news and personal updates; personal accounts are less likely to discuss policy issues; heads of state are more likely to emphasize foreign policy, and accounts posting on the country's language discuss domestic policy more often.

Our analysis here also provides strong evidence of diversionary tactics in elite communication (Hypothesis 2). Holding all else constant, leaders spend nearly half a percentage point more of their posts discussing foreign policy for each one-unit increase in social unrest. If we continue with the comparison between Poland and Venezuela as two examples of low and high levels of social unrest, our model would predict that Poland would increase the % of posts about foreign

Table 4: OLS regression of content type, aggregated by account and month

	Domestic	Foreign	Foreign (Low unrest)	Foreign (high unrest)
	(1)	(2)	(3)	(4)
Twitter (0-1)	-6.59^{***}	-1.08^{***}	-1.08^{***}	-1.06^{***}
	(0.27)	(0.28)	(0.28)	(0.28)
Personal account (0-1)	-1.94^{***}	-1.00^{***}	-1.00^{***}	-0.97^{***}
	(0.24)	(0.25)	(0.25)	(0.24)
Head of State (0-1)	-2.21^{***}	3.97^{***}	3.98^{***}	3.95^{***}
	(0.27)	(0.28)	(0.28)	(0.28)
Own language (0-1)	5.80^{***}	-4.17^{***}	-4.18^{***}	-4.20^{***}
	(0.34)	(0.35)	(0.35)	(0.35)
Unrest (log event count)	-0.14	0.43^{***}		
	(0.12)	(0.12)		
Unrest (low-level only)			0.44^{***}	
			(0.13)	
Unrest (high-level only)				0.47^{***}
				(0.13)
Democracy (0-1)	3.82^{***}	-3.11^{***}	-3.12^{***}	-3.12^{***}
	(0.30)	(0.31)	(0.31)	(0.31)
Constant	37.19^{***}	47.25^{***}	47.18^{***}	46.78^{***}
	(1.93)	(1.96)	(1.98)	(1.87)
N	14,615	14,615	14,615	14,615
Adjusted R^2	0.18	0.14	0.14	0.14
Residual Std. Error	14.27	14.47	14.47	14.47

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$. Controls (omitted from regression): GDP per capita, GDP growth, internet access, log population size, year and region fixed effects.

policy in around 1.5 percentage points if its levels of unrest were to increase to those found in Venezuela in 2016. When we disaggregate across types of unrest, we find evidence that both low and high levels lead to an increase in attention to foreign policy.

Table 4 also shows signifiant variation in rhetoric styles between democracies and autocracies. As we stated in Hypothesis 4, democratic leaders are more likely to discuss domestic policy issues than democratic leaders. The magnitude of this effect is even larger: the size of the total predicted gap is over 7 points, which corresponds to 50% of a standard deviation in the dependent variable.

To further analyze these differences, in Table **??** we report results from additional regression models where we add an interaction terms between the democracy indicator and our measure of social unrest. This allows us to examine whether democratic leaders are indeed more responsive – if that's the case, we should observe more frequent use of diversionary tactics (Hypothesis 5). As in the earlier analyses, we also disaggregate our measure of social unrest into two levels: low and high, depending on the severity of the actions.

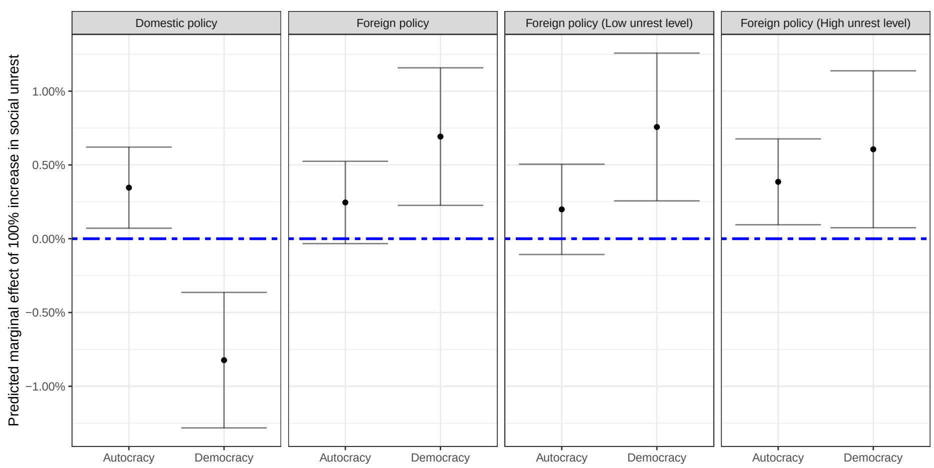
To facilitate the interpretation of the regression coefficients, in Figure 4 we plot the estimated

Table 5: OLS regression of content type, aggregated by account and month

	Domestic	Foreign	Foreign (Low unrest)	Foreign (high unrest)
	(1)	(2)	(3)	(4)
Unrest (log event count)	0.35**	0.25*		
	(0.14)	(0.14)		
Unrest (low level only)			0.20	
			(0.16)	
Unrest (high level only)				0.39***
				(0.15)
Democracy (0-1)	6.36***	−4.07***	−4.17***	−3.40***
	(0.48)	(0.49)	(0.47)	(0.40)
Democracy x Unrest	−1.17***	0.45**		
	(0.17)	(0.18)		
Democracy x Low Unrest			0.56***	
			(0.19)	
Democracy x High Unrest				0.22
				(0.20)
Constant	32.95***	48.87***	48.89***	47.39***
	(2.03)	(2.06)	(2.06)	(1.95)
N	14,615	14,615	14,615	14,615
Adjusted R^2	0.18	0.14	0.14	0.14
Residual Std. Error	14.25	14.47	14.46	14.47

*p < .1; **p < .05; ***p < .01. Controls (omitted from regression): personal account, head of state, own language, GDP per capita, internet access, logged population size, year and region fixed effects.

Figure 4: Marginal effect of social unrest on proportion of social media posts by month



marginal effect of a one-unit increase in social unrest on the dependent variable in each of our models, depending on whether the leader is in a democratic or autocratic country. Consistent with our expectations, we find that social unrest is associated with more attention to foreign policy and less to domestic policy in democracies; but not in autocracies. In other words, we only find evidence of diversionary tactics in democracies, but not in autocracies. When we disaggregate by types of social unrest, again we find that our results are robust to different metrics, and we don't find any large differences.

5 Discussion and Conclusion

Social media has become a key tool in the communication repertoire of world leaders. Anecdotal evidence of how it is increasingly used to communicate with domestic and international audiences is abundant. Its value as a tool for digital diplomacy, to broadcast messages and issue rapid responses to crises, and to manipulate the political and media agenda is now widely recognized. However, systematic empirical evidence about these new communication practices (and what motivates world leaders to engage in them) is still scarce.

The goal of this paper is to fill this gap by providing a comprehensive evaluation of how world leaders communicate on social media, as well as the institutional and political factors that explain variation in communication styles. We have provided strong evidence that support two empirical regularities. First, during contentious political times, leaders emphasize attention to foreign policy, which is consistent with theories about diversionary communication strategies. Considering that diversionary studies have been largely focused on the United States and threats of force by the U.S. presidents (Kanat, 2014), this study contributes to a more comprehensive understanding of the domestic/foreign policy nexus on a large cross-national sample. Second, we identified important differences in leader rhetoric as a function of regime type: autocratic leaders are more active on social media and post more frequently about foreign policy; however, democratic leaders are more likely to use diversionary tactics in response to social unrest, particularly so before an election. We interpret this result within the context of how democratic institutions create incentives for leaders to be accountable to their entire population; whereas autocratic leaders use social media as a tool to increase its standing in the international arena.

The breadth of the data collection and the computational methods we employed provide an unprecedented inside look into the communication strategies of governments all around the world. Our findings yield new insights on how social media is used by government actors in times of crises, and have important implications for our understanding of the impact of new technologies on how leaders communicate and interact both with the public and other international leaders.

References

Barberá, P. (2015). Birds of the same feather tweet together: Bayesian ideal point estimation using twitter data. *Political Analysis*, 23(1):76–91.

Barberá, P., Boydstun, A., Linn, S., McMahon, R., and Nagler, J. (2016). Methodological challenges in estimating tone: Application to news coverage of the us economy. In *Meeting of the Midwest Political Science Association, Chicago, IL*.

Barberá, P., Wang, N., Bonneau, R., Jost, J. T., Nagler, J., Tucker, J., and González-Bailón, S. (2015). The critical periphery in the growth of social protests. *PloS one*, 10(11):e0143611.

Barberá, P. and Zeitzoff, T. (2017). The new public address system: Why do world leaders adopt social media? *International Studies Quarterly (forthcoming)*.

Baum, M. A. and Potter, P. B. (2008). The relationships between mass media, public opinion, and foreign policy: Toward a theoretical synthesis. *Annu. Rev. Polit. Sci.*, 11:39–65.

Berinsky, A. J. (2007). Assuming the costs of war: Events, elites, and american public support for military conflict. *The Journal of Politics*, 69(4):975–997.

Brace, P. and Hinckley, B. (1992). *Follow the leader: Opinion polls and the modern presidents*. Basic Books.

Bueno de Mesquita, B. and Downs, G. W. (2005). Development and democracy. *Foreign Affairs*, 84:77.

Bursztyn, L., Egorov, G., and Fiorin, S. (2017). From extreme to mainstream: How social norms unravel. Technical report, National Bureau of Economic Research.

Cheibub, J. A., Gandhi, J., and Vreeland, J. R. (2010). Democracy and dictatorship revisited. *Public Choice*, 143(1-2):67–101.

Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the*

22nd acm sigkdd international conference on knowledge discovery and data mining, pages 785–794. ACM.

Chiozza, G. and Goemans, H. E. (2004). International conflict and the tenure of leaders: Is war still ex post inefficient? *American Journal of Political Science*, 48(3):604–619.

Clark, D. H., Fordham, B. O., and Nordstrom, T. (2011). Preying on the misfortune of others: When do states exploit their opponents' domestic troubles? *The Journal of Politics*, 73(1):248–264.

Conger, J. (1988). *Charismatic leadership*. Wiley Online Library.

Davenport, C. (2007). *State repression and the domestic democratic peace*. Cambridge University Press.

De Mesquita, B. B., Morrow, J. D., Siverson, R. M., and Smith, A. (1999). An institutional explanation of the democratic peace. *American Political Science Review*, 93(4):791–807.

De Mesquita, B. B., Morrow, J. D., Siverson, R. M., and Smith, A. (2004). Testing novel implications from the selectorate theory of war. *World Politics*, 56(03):363–388.

De Mesquita, B. B. and Smith, A. (2011). *The dictator's handbook: why bad behavior is almost always good politics*. Public Affairs.

de Mesquita, B. B., Smith, A., Siverson, R. M., and Morrow, J. D. (2005). *The Logic of Political Survival*. The MIT Press, 1 edition.

De Vries, E., Schoonvelde, M., and Schumacher, G. (2018). No longer lost in translation: Evidence that google translate works for comparative bag-of-words text applications. *Political Analysis*, 26(4):417–430.

D'Orazio, V. and Yonamine, J. E. (2015). Kickoff to conflict: A sequence analysis of intra-state conflict-preceding event structures. *PLOS ONE*, 10(5):1–21.

Garver, E. (1994). *Aristotle's Rhetoric: An art of character*. University of Chicago Press.

Geddes, B., Wright, J., and Frantz, E. (2018). *How dictatorships work: Power, personalization, and collapse*. Cambridge University Press.

Gelpi, C. (1997). Democratic diversions: Governmental structure and the externalization of domestic conflict. *Journal of Conflict Resolution*, 41(2):255–282.

Gohdes, A. R. (2015). Pulling the plug network disruptions and violence in civil conflict. *Journal of Peace Research*, 52(3):352–367.

Grimmer, J., Westwood, S. J., and Messing, S. (2014). *The impression of influence: legislator communication, representation, and democratic accountability*. Princeton University Press.

Guisinger, A. and Saunders, E. N. (2017). Mapping the boundaries of elite cues: How elites shape mass opinion across international issues. *International Studies Quarterly*, 61(2):425–441.

Gunitsky, S. (2015). Corrupting the cyber-commons: Social media as a tool of autocratic stability. *Perspectives on Politics*, 13(1):42–54.

Hagan, J. D. (1986). Domestic political conflict, issue areas, and some dimensions of foreign policy behavior other than conflict. *International Interactions*, 12(4):291–313.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). Overview of supervised learning. In *The elements of statistical learning*, pages 9–41. Springer.

Horowitz, M. C., Stam, A. C., and Ellis, C. M. (2015). *Why leaders fight*. Cambridge University Press.

Howard, P. N., Duffy, A., Freelon, D., Hussain, M. M., Mari, W., and Mazaid, M. (2011). Opening closed regimes: what was the role of social media during the arab spring? *Available at SSRN 2595096*.

Jagers, J. and Walgrave, S. (2007). Populism as political communication style: An empirical study of political parties' discourse in belgium. *European Journal of Political Research*, 46(3):319–345.

James, P. (1988). *Crisis and war*. McGill-Queen's Press-MQUP.

Kalmoe, N. P. (2014). Fueling the fire: Violent metaphors, trait aggression, and support for political violence. *Political Communication*, 31(4):545–563.

Kalmoe, N. P., Gubler, J. R., and Wood, D. A. (2017). Toward conflict or compromise? how violent metaphors polarize partisan issue attitudes. *Political Communication*, pages 1–20.

Kam, C. D. and Ramos, J. M. (2008). Joining and leaving the rally: Understanding the surge and decline in presidential approval following 9/11. *Public Opinion Quarterly*, 72(4):619–650.

Kanat, K. B. (2014). Diversionary foreign policy in authoritarian states: The use of multiple diversionary strategies by saddam hussein during the gulf war. *Journal of Strategic Security*, 7(1):16.

Keller, F. B., Schoch, D., Stier, S., and Yang, J. (2017). How to manipulate social media: Analyzing political astroturfing using ground truth data from south korea. In *Eleventh International AAAI*

Conference on Web and Social Media.

Kertzer, J. D. and Zeitzoff, T. (2017). A bottom-up theory of public opinion about foreign policy. *American Journal of Political Science*, 61(3):543–558.

King, G., Pan, J., and Roberts, M. E. (2013). How censorship in china allows government criticism but silences collective expression. *American Political Science Review*, 107(2):326–343.

Krebs, R. R. (2015). *Narrative and the making of US national security*, volume 138. Cambridge University Press.

Krebs, R. R. and Jackson, P. T. (2007). Twisting tongues and twisting arms: The power of political rhetoric. *European Journal of International Relations*, 13(1):35–66.

Lakoff, G. and Johnson, M. (2008). *Metaphors we live by*. University of Chicago press.

Lasswell, H. D. (1948). The structure and function of communication in society. *The communication of ideas*, 37:215–228.

Lucas, C., Nielsen, R. A., Roberts, M. E., Stewart, B. M., Storer, A., and Tingley, D. (2015). Computer-assisted text analysis for comparative politics. *Political Analysis*, 23(2):254–277.

Marra, R. F., Ostrom Jr, C. W., and Simon, D. M. (1990). Foreign policy and presidential popularity: Creating windows of opportunity in the perpetual election. *Journal of Conflict Resolution*, 34(4):588–623.

Marshall, M. G., Gurr, T. R., and Jaggers, K. (2017). Polity iv project: Political regime characteristics and transitions, 1800-2016.

Metternich, N. W., Dorff, C., Gallop, M., Weschle, S., and Ward, M. D. (2013). Antigovernment networks in civil conflicts: How network structures affect conflictual behavior. *American Journal of Political Science*, pages n/a–n/a.

Miller, R. A. (1999). Regime type, strategic interaction, and the diversionary use of force. *Journal of Conflict Resolution*, 43(3):388–402.

Morgan, T. C. and Anderson, C. J. (1999). Domestic support and diversionary external conflict in great britain, 1950-1992. *The Journal of Politics*, 61(3):799–814.

Morgan, T. C. and Bickers, K. N. (1992). Domestic discontent and the external use of force. *Journal of Conflict Resolution*, 36(1):25–52.

Morozov, E. (2012). *The net delusion: The dark side of Internet freedom*. PublicAffairs.

Mukunda, G. (2012). *Indispensable: When leaders really matter*. Harvard Business Press.

Munger, K., Bonneau, R., Nagler, J., and Tucker, J. A. (2018). Elites tweet to get feet off the streets: Measuring regime social media strategies during protest. *Political Science Research and Methods*, pages 1–20.

Nithyanand, R., Schaffner, B., and Gill, P. (2017). Online political discourse in the trump era. *arXiv preprint arXiv:1711.05303*.

O'brien, S. P. (2010). Crisis early warning and decision support: Contemporary approaches and thoughts on future research. *International studies review*, 12(1):87–104.

Olson, M. (1993). Dictatorship, democracy, and development. *American political science review*, 87(3):567–576.

Olson, R. S., La Cava, W., Mustahsan, Z., Varik, A., and Moore, J. H. (2017). Data-driven advice for applying machine learning to bioinformatics problems. *arXiv preprint arXiv:1708.05070*.

Pennebaker, J. W. (2013). *The Secret Life of Pronouns: What Our Words Say About Us*. Bloomsbury Publishing USA.

Roberts, M. E. (2018). *Censored: Distraction and Diversion Inside Chinas Great Firewall*. Princeton University Press.

Rozenas, A. and Stukal, D. (2018). How autocrats manipulate economic news: Evidence from russia's state-controlled television. *Journal of Politics*, Forthcoming.

Russett, B. (1990). Economic decline, electoral pressure, and the initiation of interstate conflict. *Prisoners of war*, pages 123–40.

Schrodt, P. A. (2012). Cameo: Conflict and mediation event observations event and actor codebook. *Pennsylvania State University*.

Selb, P. and Munzert, S. (2018). Examining a most likely case for strong campaign effects: Hitlers speeches and the rise of the nazi party, 1927–1933. *American Political Science Review*, 112(4):1050–1066.

Siegel, N. (2018). Political norms, constitutional conventions, and president donald trump.

Simmel, G. (1955). Conflict (kh wolff, trans.). *Glencoe, IL: The Free Press.(Original work published*

1908).

Sobek, D. (2007). Rallying around the podesta: Testing diversionary theory across time. *Journal of Peace Research*, 44(1):29–45.

Sprecher, C. and DeRouen Jr, K. (2002). Israeli military actions and internalization-externalization processes. *Journal of Conflict Resolution*, 46(2):244–259.

Steinert-Threlkeld, Z. C. (2017). Spontaneous collective action: Peripheral mobilization during the arab spring. *American Political Science Review*, 111(2):379–403.

Theocharis, Y., Barberá, P., Fazekas, Z., Popa, S. A., and Parnet, O. (2016). A bad workman blames his tweets: The consequences of citizens' uncivil twitter use when interacting with party candidates. *Journal of Communication*.

Tucker, J. A., Theocharis, Y., Roberts, M. E., and Barberá, P. (2017). From liberation to turmoil: social media and democracy. *Journal of democracy*, 28(4):46–59.

Tufekci, Z. and Wilson, C. (2012). Social media and the decision to participate in political protest: Observations from tahrir square. *Journal of Communication*, 62(2):363–379.

Van Vugt, M., Hogan, R., and Kaiser, R. B. (2008). Leadership, followership, and evolution: some lessons from the past. *American Psychologist*, 63(3):182.

Voigtländer, N. and Voth, H.-J. (2015). Nazi indoctrination and anti-semitic beliefs in germany. *Proceedings of the National Academy of Sciences*, 112(26):7931–7936.

Way, L. A. and Levitsky, S. (2006). The dynamics of autocratic coercion after the cold war. *Communist and Post-Communist Studies*, 39(3):387–410.

Wedeen, L. (2015). *Ambiguities of domination: Politics, rhetoric, and symbols in contemporary Syria*. University of Chicago Press.

Weeks, J. L. (2014). *Dictators at war and peace*. Cornell University Press.

Weidmann, N. B. (2015). Communication, technology, and political conflict introduction to the special issue. *Journal of Peace Research*, 52(3):263–268.

Weiss, J. and Dafoe, A. (2018). Authoritarian audiences and government rhetoric in international crises: Evidence from china. *Working Paper*.

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the rwandan genocide. *The*

Quarterly Journal of Economics, 129(4):1947–1994.

Zeitzoff, T. (2016). Does social media influence conflict? evidence from the 2012 gaza conflict. *Journal of Conflict Resolution*.

Zeitzoff, T., Kelly, J., and Lotan, G. (2015). Using social media to measure foreign policy dynamics: An empirical analysis of the iranian–israeli confrontation (2012–13). *Journal of Peace Research*, 52(3):368–383.

Appendix A Examples of tweets by Mauricio Macri

Figure A1: President Macri Tweets (September 25-26)

Appendix B Classifier performance across different subsets of the data

Table B1: Out-of-sample performance of machine learning classifiers across languages

All posts (N=6,000)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.722	0.654	0.633	38.8%
Foreign policy	0.782	0.671	0.644	31.2%

Posts in English (N=2,050)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.731	0.611	0.496	26.7%
Foreign policy	0.788	0.736	0.646	31.9%

Posts in other languages (N=3,950)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.718	0.667	0.686	44.2%
Foreign policy	0.779	0.637	0.642	30.8%

Table B2: Out-of-sample performance of machine learning classifiers across platforms

All posts (N=6,000)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.722	0.654	0.633	38.8%
Foreign policy	0.782	0.671	0.644	31.2%

Tweets (N=3,025)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.713	0.592	0.505	29.0%
Foreign policy	0.760	0.672	0.614	32.0%

Facebook posts (N=2,975)

Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.732	0.691	0.730	47.5%
Foreign policy	0.803	0.670	0.678	30.3%

Appendix C Descriptive statistics

Table C3: Summary statistics: data at the account-month level

Statistic	N	Mean	Min	Pctl(25)	Median	Pctl(75)	Max
Social media posts (total)	14,922	53.92	1	13	30	62	1,490
Tweets	8,824	63.29	1.00	15.00	35.00	75.00	1,490.00
Facebook posts	6,098	40.36	1.00	11.00	26.00	49.00	940.00
Social unrest (total)	14,922	29.65	0	1	6	23	1,744
Social unrest (low level)	14,922	19.96	0	1	4	14	1,233
Social unrest (high level)	14,922	9.69	0	0	1	7	511
% domestic policy	14,922	46.94	0.00	36.91	46.85	56.90	100.00
% foreign policy	14,922	30.67	0.00	19.62	28.17	39.64	100.00
% democratic countries	14,922	48.67	0	0	0	100	100
GDP per capita (log)	14,615	9.59	6.39	8.94	9.79	10.43	11.72
GDP growth	14,771	3.12	-16.68	1.62	2.99	4.65	26.68
% of internet users	14,871	57.23	0.00	35.14	63.25	79.00	98.14
Population (log)	14,922	16.41	13.15	15.46	16.27	17.52	21.02
Days until next election	3,504	613.32	1.00	236.00	532.65	924.10	2,025.10

Appendix D Robustness

Table D4: OLS regression of monthly post counts by account

	(1)	(2)	(3)	(4)	(5)
Twitter (0-1)	0.31***	0.31***	0.31***	0.31***	0.31***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Personal account (0-1)	−0.54***	−0.55***	−0.55***	−0.54***	−0.54***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Head of State (0-1)	−0.01	0.001	−0.002	0.004	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Own language (0-1)	0.33***	0.29***	0.30***	0.29***	0.29***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Unrest (log event count)	−0.01				
	(0.02)				
Unrest^2	0.02***				
	(0.004)				
Unrest (disapprove/reject)		0.09***			
		(0.01)			
Unrest (statement/appeal)			0.09***		
			(0.01)		
Unrest (threaten/protest)				0.10***	
				(0.01)	
Unrest (coerce/assault/fight)					0.10***
					(0.01)
Democracy (0-1)	−0.15***	−0.14***	−0.13***	−0.15***	−0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	1.90***	1.41***	1.63***	1.36***	1.53***
	(0.24)	(0.24)	(0.24)	(0.23)	(0.24)
N	14,615	14,615	14,615	14,615	14,615
Adjusted R^2	0.16	0.16	0.16	0.16	0.16
Residual Std. Error	1.13	1.13	1.13	1.13	1.13

*p $<$ .1; **p $<$ .05; ***p $<$ .01. Controls (omitted from regression): GDP per capita, GDP growth, internet access, log population size, year and region fixed effects.

Table D5: OLS regression of monthly post counts by account (Only autocracies)

	All autocracies	Military	Monarchy	Party	Personal
	(1)	(2)	(3)	(4)	(5)
Twitter (0-1)	0.26***	−0.001	0.91***	0.30***	0.23***
	(0.04)	(0.15)	(0.11)	(0.05)	(0.05)
Personal account (0-1)	−0.53***	−0.23	−0.54***	−0.40***	−0.68***
	(0.03)	(0.21)	(0.09)	(0.05)	(0.04)
Head of State (0-1)	0.04	0.96*	−0.68***	−0.18***	0.28***
	(0.04)	(0.56)	(0.10)	(0.05)	(0.05)
Own language (0-1)	0.04	1.25*	−0.90***	0.39***	0.28***
	(0.05)	(0.66)	(0.19)	(0.08)	(0.06)
Unrest (log event count)	0.10***	0.21***	−0.02	0.01	0.01
	(0.02)	(0.07)	(0.05)	(0.03)	(0.02)
Constant	2.38***	−21.67	0.84	−0.77	0.43
	(0.43)	(15.92)	(1.77)	(0.72)	(0.63)
N	4,653	216	864	2,478	2,618
Adjusted R^2	0.11	0.50	0.22	0.14	0.18
Residual Std. Error	1.13	0.74	1.17	1.12	1.02

*p $<$ .1; **p $<$ .05; ***p $<$ .01. Controls (omitted from regression): GDP per capita, GDP growth, internet access, log population size, year and region fixed effects.

Table D6: OLS regression of monthly post counts by account (Time-Series Cross-Section Analysis

	(1)	(2)	(3)
Lagged DV	0.74^{***}	0.76^{***}	0.74^{***}
	(0.01)	(0.01)	(0.01)
Twitter (0-1)	0.03^{**}	0.03^{**}	0.10^{***}
	(0.02)	(0.01)	(0.02)
Personal account (0-1)	-0.15^{***}	-0.14^{***}	-0.14^{***}
	(0.01)	(0.01)	(0.01)
Head of State (0-1)	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)
Own language (0-1)	0.10^{***}	0.09^{***}	0.10^{***}
	(0.02)	(0.02)	(0.02)
Unrest (log event count)	0.03^{***}	0.03^{***}	0.02^{**}
	(0.01)	(0.01)	(0.01)
Unrest (1-month lag)		-0.01	-0.01
		(0.01)	(0.01)
Unrest (2-month lag)		0.01	0.01
		(0.01)	(0.01)
Unrest (1-month lead)			0.02^{*}
			(0.01)
Unrest (2-month lead)			0.001
			(0.01)
Democracy (0-1)	-0.01	-0.02	-0.03
	(0.02)	(0.02)	(0.02)
Constant	0.59^{***}	0.52^{***}	0.51^{***}
	(0.17)	(0.17)	(0.17)
N	14,117	13,622	12,668
Adjusted R^2	0.61	0.62	0.62
Residual Std. Error	0.77	0.75	0.73

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$. Controls (omitted from regression): GDP per capita, GDP growth, internet access, log population size, year and region fixed effects.