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

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Instituto Carlos III – Juan March
March 8th, 2019

World leaders on social media

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UK Prime Minister
@Number10gov
Follow

PM: I would reassure markets and investors that Britain’s economy is fundamentally strong. #EURefResults

Dmitry Medvedev
@MedvedevRussiaE
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The EU has decided to extend its anti-Russia sanctions. Russia will extend its response measures through 2018

6:03 AM - 29 Jun 2017

101 Retweets 197 Likes

74 101 197

Recep Tayyip Erdoğan
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Donald J. Trump @realDonaldTrump

Follow

Just heard Foreign Minister of North Korea speak at U.N. If he echoes thoughts of Little Rocket Man, they won't be around much longer!

6:08 AM - 24 Sep 2017

35,881 Retweets 131,589 Likes

World leaders on social media

WORLD NEWS DECEMBER 12, 2017 / 6:18 AM / 2 MONTHS AGO

REUTERS

Kremlin: We see Trump's tweets as official statements

Trump's Twitter Threats Put American Credibility on the Line

Leer en español

The New York Times

By STEVEN ERLANGER JAN. 7, 2018

World leaders on social media

Known effects of elite rhetoric

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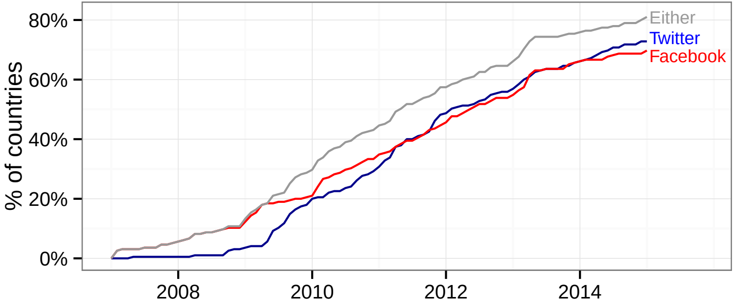
- Elite hate speech can lead to actual violence–e.g., Hutu Power Radio Station in Rwanda (Yanagizawa-Drott, 2014)
- Political incivility follows elite incivility, e.g. Post-Trump US blogosphere (Nithyanand et al., 2017, but see Siegel et al, 2018)

World leaders on social media



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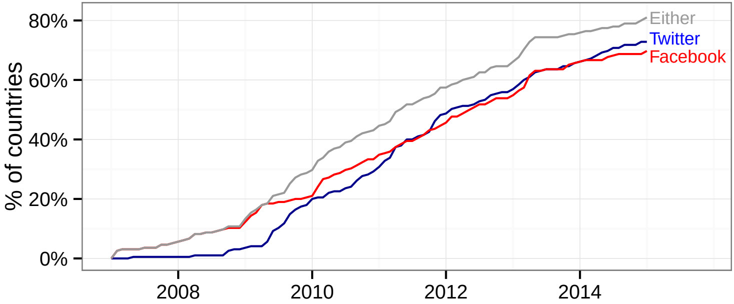

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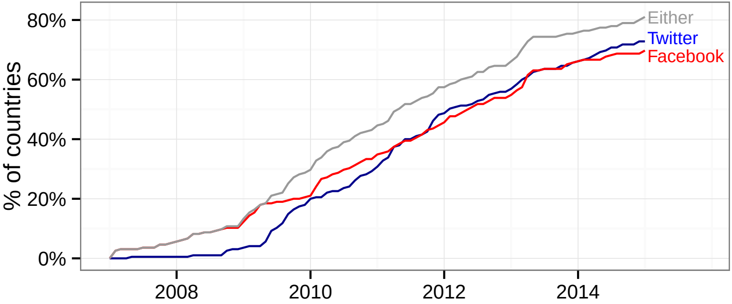

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- Adoption increases after episodes of social unrest
- Leaders in democracies more likely to use social media

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What explains how world leaders use social media?

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- Diversionary tactics in contexts of contentious politics

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- Diversionary tactics in contexts of contentious politics
- Role of institutions

Diversionary theory of foreign policy

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Empirical expectations:

- During episodes of social unrest...
- ...leaders will *increase* (1) attention to foreign policy and (2) overall social media activity

Responsiveness in the context of elections (in democracies)

(de Mesquita et al, 2005)

Mechanism: Democratic leaders cater to a broader constituency, which increases need for responsiveness

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Empirical expectations:

- Democratic leaders will (1) be *more* active on social media, (2) focus attention on *domestic* policy...
- ...(3) be *more responsive* to social unrest, and (4) particularly so *before an election*

A new dataset

- Twitter and Facebook accounts of the heads of state and heads of government of all 193 U.N. member countries.

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- Both institutional and personal accounts
- Both English-language accounts and own language
- Updated as of August 2016
- All Tweets and Facebook posts from Jan 1, 2012 to Jun 1, 2017, collected from public APIs
- Current total: 285,414 Facebook posts & 609,224 tweets

Classifying social media posts

For each social media post:

- Content type (supervised machine learning):
  1. Domestic policy
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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%
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.

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- Apply to full sample of social media posts

N-grams with highest feature importance, weighted by frequency

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

Supervised learning classification

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All posts (N=6,000)

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Posts in English (N=2,050)

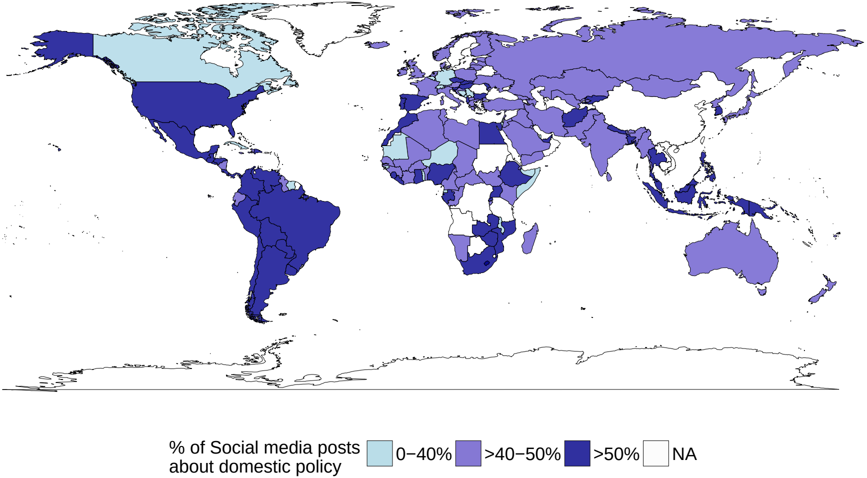
Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.731	0.611	0.496	26.7%
Foreign policy	0.788	0.736	0.646	31.9%

Posts in other languages (N=3,950)

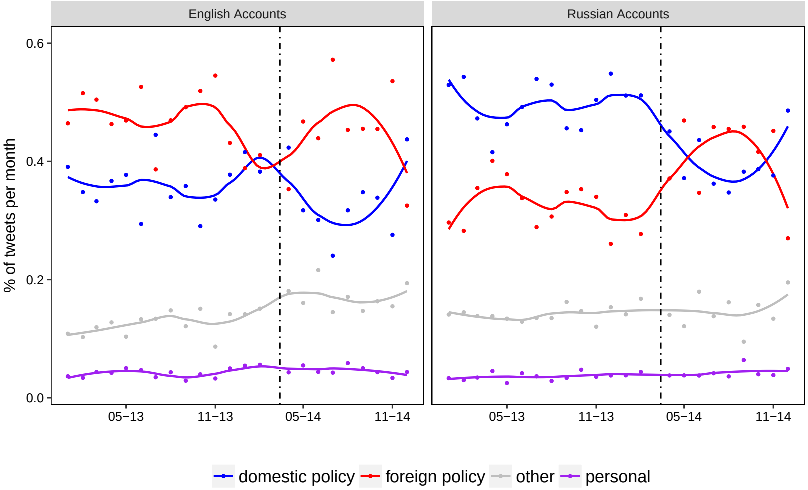
Category	Accuracy	Precision	Recall	Baseline
Domestic policy	0.718	0.667	0.686	44.2%
Foreign policy	0.779	0.637	0.642	30.8%

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.

% of social media posts that deal with domestic issues



Russia, during the Crimea crisis, by audience



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Month level index of **social unrest** using ICEWS:

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- All countries except USA

Additional variables

Social media dataset was then merged with:

- **Democracy** indicator from Polity IV at year level
- **GDP per capita**, **GDP growth**, **Internet access**, **population** at year level from World Bank development indicators
- **Days until next election**, presidential or legislative, from ElectionGuide, at month level
- **Region fixed-effects**

Predictors of social media activity

DV = log monthly post count (OLS)
Mean = log(54), Std. Dev. = 1.15
Controls: GDPpc, growth, internet, log population, year and region fixed effects
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

	Full sample
N	14,615
Adjusted R^2	0.16
Constant	1.66^{***}
	(0.24)
Twitter (0-1)	0.31^{***}
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Own language (0-1)	0.31^{***}
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Unrest (log event count)	0.09^{***}
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Diversionary theory:

- Social media activity increases during episodes of social unrest
- Effect is somewhat larger for high-level unrest

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Institutional factors:

- Autocratic leaders are more active on social media

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	Democracies
N	2,805
Adjusted R^2	0.20
Constant	3.87***
	(0.62)
...	...
	...
Unrest (log event count)	0.22***
	(0.08)
Days until election (log)	0.01
	(0.04)
Unrest x Days til elec.	−0.03**
	(0.01)

Diversionary theory:

- Social media activity increases during episodes of social unrest
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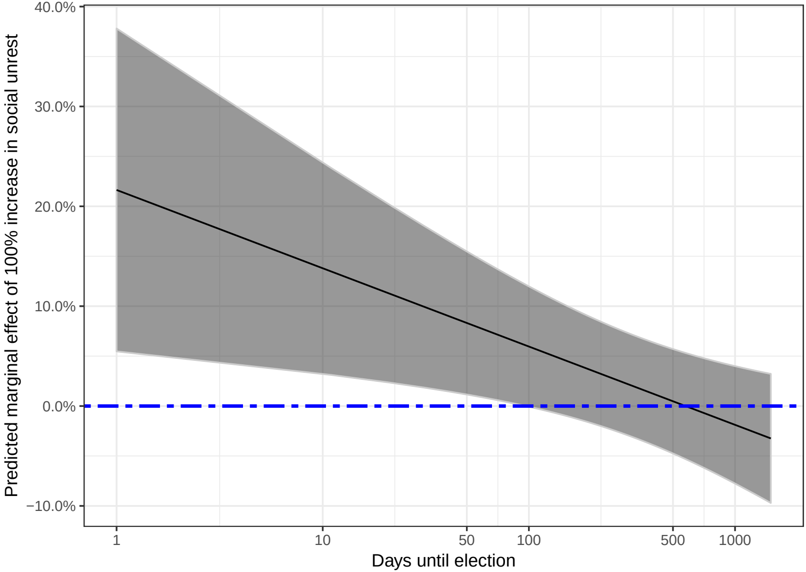
Institutional factors:

- Autocratic leaders are more active on social media
- In democracies, positive effect of social unrest on leaders' activity is greater when elections are near

Predictors of social media activity



Predictors of rhetoric style

Table: OLS regression of content type proportion, at month level

	Domestic	Foreign
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	(1.93)	(1.96)
N	14,615	14,615
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DVs: Month-level averages of predicted probabilities that social media post is about domestic/foreign policy (Models 1-2)

Controls: GDPpc, account type, internet usage, population, year/region fixed effects

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	(0.27)	(0.28)
Head of State (0-1)	−2.21***	3.97***
	(0.27)	(0.28)
Own language (0-1)	5.80***	−4.17***
	(0.34)	(0.35)
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	(0.12)	(0.12)
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Unrest (log event count)	−0.14	0.43***
	(0.12)	(0.12)
Democracy (0-1)	3.82***	−3.11***
	(0.30)	(0.31)
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Controls: GDPpc, account type, internet usage, population, year/region fixed effects

How regime type affect responses to social unrest

Table: OLS regression of content type, aggregated by month

	Domestic	Foreign
	(1)	(2)
Constant	32.95***	48.87***
	(2.03)	(2.06)
	...	...
Unrest (log event count)	0.35**	0.25*
	(0.14)	(0.14)
Democracy (0-1)	6.26***	−4.07***
	(0.48)	(0.49)
Democracy x Unrest	−1.17***	0.45**
	(0.17)	(0.18)
N	14,615	14,615
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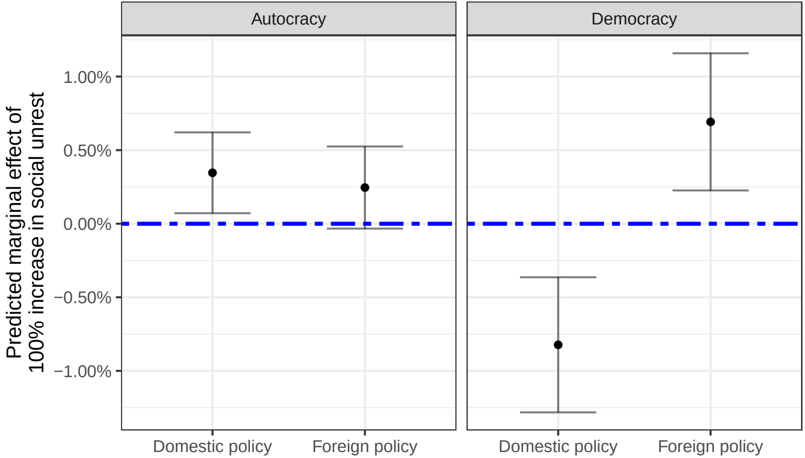
*p $<$ .1; **p $<$ .05; ***p $<$ .01

DVs: Month-level averages of predicted probabilities that social media post is about domestic or foreign policy (Models 1-2)
Controls: GDPpc, account type, account actor, internet usage, population, platform, GDP growth, year/region fixed effects

Predictors of rhetoric style



Summary of results

Diversionary communication strategies

- **Social unrest** is associated with more attention to foreign policy and overall social media activity

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Institutional effects

- **Democratic leaders** are less active on social media, but post more frequently about domestic policy
- They are more likely to use diversionary tactics in response to social unrest, particularly so before an election

Next Steps

- Dynamics at different aggregation levels

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- How leader rhetoric affects social unrest

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- Other thoughts?

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

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Thank you!