The Returns to Viral Media: The Case of US Political Donations

Johannes Böken, University of Warwick
Mirko Draca, University of Warwick
Nicola Mastorocco, University of Bologna
Arianna Ornaghi, Hertie School

May 2023

An evolving media landscape

- Social media represents a major structural change in mass communication

An evolving media landscape

- Social media represents a major structural change in mass communication
- In contrast with the concentrated, top-down broadcast model of 20th century and earlier, social media is...
  - Massively "multi-channel" because of low barriers to entry
  - Characterized by very fast endogenous feedback and transmission

An evolving media landscape

- Social media represents a major structural change in mass communication
- In contrast with the concentrated, top-down broadcast model of 20th century and earlier, social media is...
  - Massively "multi-channel" because of low barriers to entry
  - Characterized by very fast endogenous feedback and transmission
- These features imply lots of competition plus a new role for behavioral biases

What social media means for political communication

- Social media has taken on an important role in political communication
  - Can be used to deliver advertising, persuade voters, and mobilize supporters

What social media means for political communication

- Social media has taken on an important role in political communication
  - Can be used to deliver advertising, persuade voters, and mobilize supporters
- We focus on supporters' mobilization and ask if politicians can translate the attention they receive online in something they care about: campaign donations
  - Political donations offer direct financial metric to estimate the returns to attention

What social media means for political communication

- Social media has taken on an important role in political communication
  - Can be used to deliver advertising, persuade voters, and mobilize supporters
- We focus on supporters' mobilization and ask if politicians can translate the attention they receive online in something they care about: campaign donations
  - Political donations offer direct financial metric to estimate the returns to attention
- Research question: what is the return to attention on (political) social media?
  - How do returns vary with the level of attention?
  - Is this a distributed or winner-takes-all market?
  - What type of messages are better at generating these returns? [coming soon!]

A one slide summary of the paper

- We study US Members of Congress (MOCs) in 2019-2020

A one slide summary of the paper

- We study US Members of Congress (MOCs) in 2019-2020
- We estimate donations-campaign relationship using MOC-by-date panel, and move towards causality exploiting geographic variation in Twitter usage

A one slide summary of the paper

- We study US Members of Congress (MOCs) in 2019-2020
- We estimate donations-campaign relationship using MOC-by-date panel, and move towards causality exploiting geographic variation in Twitter usage
- We find that...
  - Twitter likes are positively related to donations, but magnitude is modest
  - This masks substantial heterogeneity, as returns are highly skewed
  - Consistent with causality, the result is driven by high-Twitter-usage states

Setting

How big is the attention channel on Twitter?

- For us to find an effect, Twitter must be a significant media channel
  - Twitter ranks 6th in US website traffic statistics (at least, it did in 2021...)
  - It has a reach comparable to that of cable news

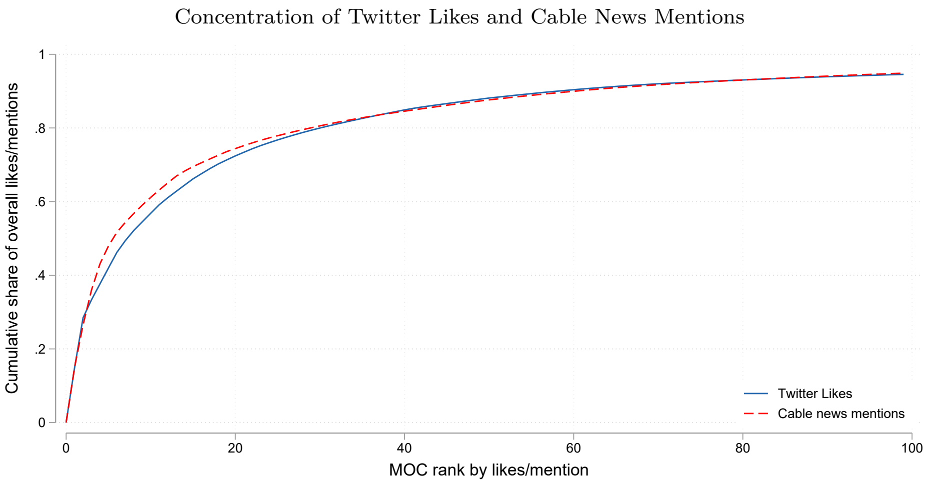
How big is the attention channel on Twitter?

- For us to find an effect, Twitter must be a significant media channel
  - Twitter ranks 6th in US website traffic statistics (at least, it did in 2021...)
  - It has a reach comparable to that of cable news

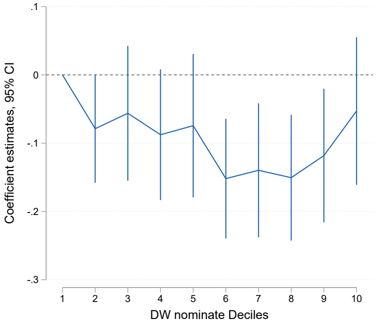
- Twitter users are a very relevant population to think about campaign donations, as they are more likely to donate to candidates then the general population

	No Twitter	Some Twitter	Daily Twitter	Total
Donation (candidate)	13.8 %	18.2 %	25.1 %	16.0 %
Income >$100k	37.2 %	51.4 %	51.1 %	41.8 %
College	29.9 %	47.1 %	47.0 %	35.4 %
City	30.1 %	31.3 %	35.4 %	30.9 %
Democrat	48.2 %	55.2 %	72.0 %	52.5 %
Share	68.0 %	20.8 %	11.2 %	100 %

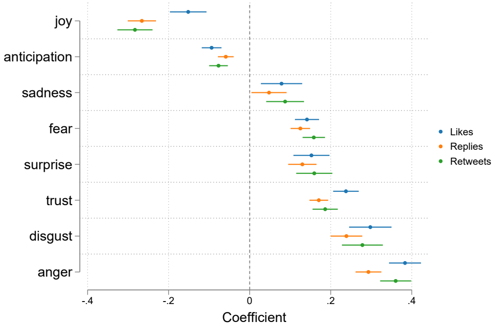
Twitter attention is similarly concentrated as cable news



What goes viral?



(a) Likes by Ideology



(b) Likes by Sentiment

Data

Data

- Comprehensive dataset of Twitter activity of MOCs in 116th Congress
  - Includes all Tweets and the respective metrics for 506 MOCs Jan 2019-Oct 2020

Data

- Comprehensive dataset of Twitter activity of MOCs in 116th Congress
  - Includes all Tweets and the respective metrics for 506 MOCs Jan 2019-Oct 2020
- Individual campaign contributions from public FEC dataset
  - Includes all direct and indirect donations
  - Focus on small donations, i.e. donations <$1000

Data

- Comprehensive dataset of Twitter activity of MOCs in 116th Congress
  - Includes all Tweets and the respective metrics for 506 MOCs Jan 2019-Oct 2020
- Individual campaign contributions from public FEC dataset
  - Includes all direct and indirect donations
  - Focus on small donations, i.e. donations <$1000
- Mentions of MOCs in cable news channels from the Internet Archive's transcripts

Returns to Twitter attention

Baseline specification for MOC-level analyses

- We begin by investigating the relationship between attention on Twitter and donations estimating the following specification on a MOC-by-date panel:

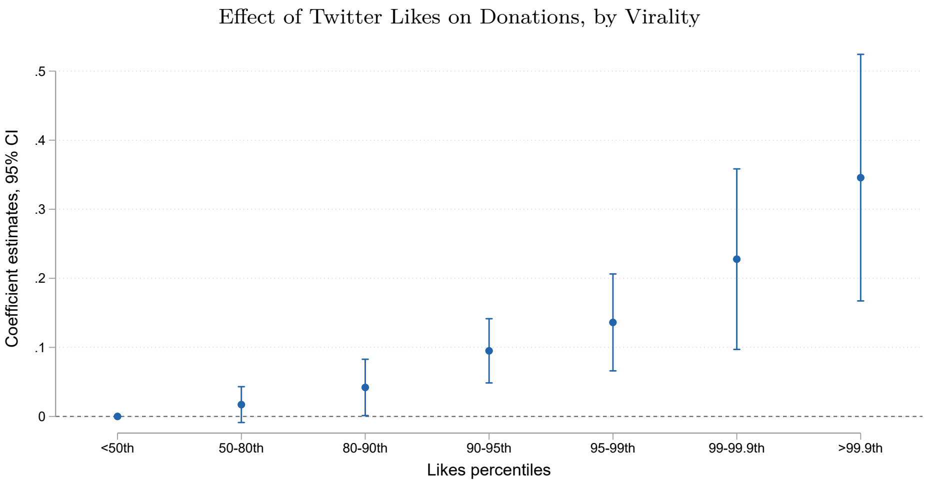
$$y_{it} = \beta likes_{it} + \alpha_{im(t)} + \tau_{p(i)t} + \epsilon_{it},$$

  - y_{it} is the log+1 of the aggregate small contribution to MOC i on day t
  - $likes_{it}$ is the log+1 average likes per tweet of MOC i on day t
  - $\alpha_{im(t)}$ are MOC by month fixed effects
  - $\tau_{p(i)t}$ are party by day fixed effects
  - Standard errors are clustered at the MOC level

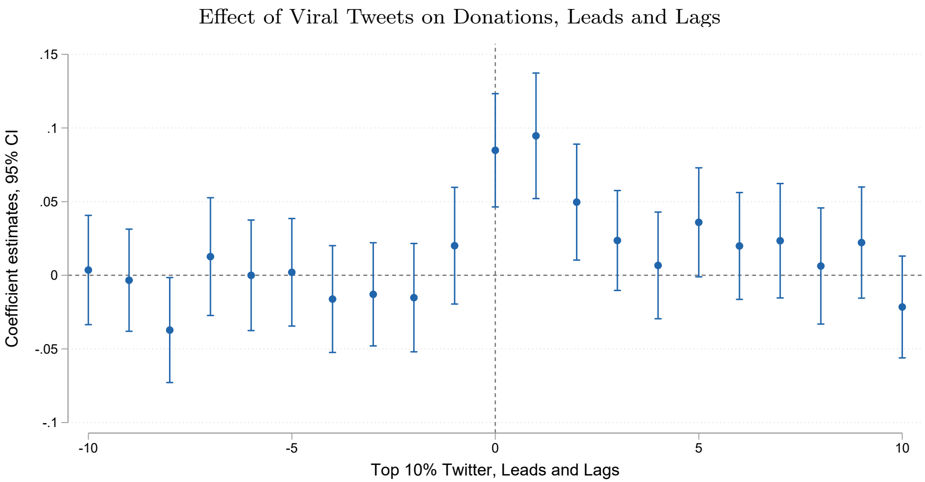
There are positive returns to attention on social media

	(1)	(2)	(3)	(4)
	Small donations			Small donors
Likes	0.362***	0.326***	0.011***	0.004***
	(0.022)	(0.025)	(0.003)	(0.001)
ID FE	X	X	X	X
Date FE	X	X	X	X
Date X Party FE		X	X	X
ID X Month FE			X	X
Observations	339,020	339,020	339,020	339,020
# Clusters: *MOC*	506	506	506	506

Returns to attention are highly skewed



Estimating leads and lags shows minimal anticipation effects



The attention shock seems to go beyond the news cycle

	(1)	(2)	(3)	(4)	(5)
	Small donations				
Likes	0.011***		0.010***		
	(0.003)		(0.003)		
Cable mentions		0.062***	0.058***		
		(0.014)	(0.014)		
ID X month FE	X	X	X		
Date X Party FE	X	X	X		
Observations	339,020	339,020	339,020		
# Clusters: *MOC*	506	506	506		

Returns to attention on Twitter and cable news are comparable

	(1)	(2)	(3)	(4)	(5)
	Small donations			Small donations	
Likes	0.011***		0.010***		
	(0.003)		(0.003)		
Cable mentions		0.062***	0.058***		
		(0.014)	(0.014)		
Top 10% Twitter				0.086***	0.081***
				(0.019)	(0.019)
Top 10% TV					0.077***
					(0.021)
ID X month FE	X	X	X	X	X
Date X Party FE	X	X	X	X	X
Observations	339,020	339,020	339,020	339,020	339,020
# Clusters: *MOC*	506	506	506	506	506

Making sense of the magnitudes

- A viral day increases donations by 8.1%, which corresponds to \$98 at the mean
  - The top-5 MOCs by number of likes go viral 605 days on average, relative to 31 days for those outside the top-50 → the top-5 MOCs earn an additional \$55k

Making sense of the magnitudes

- A viral day increases donations by 8.1%, which corresponds to \$98 at the mean
  - The top-5 MOCs by number of likes go viral 605 days on average, relative to 31 days for those outside the top-50 → the top-5 MOCs earn an additional \$55k
- The persuasion rate is ∼1.45%, similar to that of opening a Twitter account (Petrova et al. (2021)) and of political ads (Spenkuch and Toniatti (2018))

Making sense of the magnitudes

- A viral day increases donations by 8.1%, which corresponds to $98 at the mean
  - The top-5 MOCs by number of likes go viral 605 days on average, relative to 31 days for those outside the top-50 → the top-5 MOCs earn an additional $55k
- The persuasion rate is ∼1.45%, similar to that of opening a Twitter account (Petrova et al. (2021)) and of political ads (Spenkuch and Toniatti (2018))
- Even if MOCs at the extremes of the ideological spectrum receive more likes, these differences are not sufficient to explain differences in donations

Geography-based design

Moving towards causality

- Our preferred specification is quite restrictive, but the donation-likes relationship might still be driven by other activities of the MOCs beyond Twitter
  - There could be attention shocks that are not well proxied by cable news
  - IRL activities such as rallies might influence both donations and likes

Moving towards causality

- Our preferred specification is quite restrictive, but the donation-likes relationship might still be driven by other activities of the MOCs beyond Twitter
  - There could be attention shocks that are not well proxied by cable news
  - IRL activities such as rallies might influence both donations and likes
- We test whether the increase in donation comes exactly from those states in which Twitter is more prominent (namely, states with a higher number of users)

Moving towards causality

- Our preferred specification is quite restrictive, but the donation-likes relationship might still be driven by other activities of the MOCs beyond Twitter
  - There could be attention shocks that are not well proxied by cable news
  - IRL activities such as rallies might influence both donations and likes
- We test whether the increase in donation comes exactly from those states in which Twitter is more prominent (namely, states with a higher number of users)
- Looking at heterogeneous effects also allows us to estimate even more restrictive specification, for example including MOC-by-day fixed effects

Baseline specification for geography-based analysis

- We estimate the following specification using a MOC-by-state-by-date panel:

$$y_{ist} = \beta likes_{it} \times users_s + \delta_{ism(t)} + \tau_{it} + \theta_{st} + \varepsilon_{ist}$$

  - y_{ist} is the log+1 of the aggregate small contribution to MOC i on day t from state s
  - $likes_{it}$ is the log+1 average likes per tweet of MOC i on day t
  - $users_s$ is the log+1 number of Twitter users in state s
  - $\delta_{ism(t)}$ are MOC by state by month fixed effects
  - τ_{it} are MOC by day fixed effects
  - θ_{st} are state by day fixed effects
  - Standard errors are clustered at the MOC and state level

High-Twitter intensity states respond more to the shock

	(1)	(2)
	Small donations	
Likes X Twitter use	0.001***	0.001***
	(0.000)	(0.000)
Pair X Month FE	X	X
ID X Date FE	X	X
State X Date FE	X	X
Controls		X
Obs. (million)	16.6	16.6
# Clusters: *MOC*	506	506
# Clusters: *State*	49	49

An instrumental variable strategy

- This is reassuring, but we might still be worried of the heterogeneity picking up differences across states (e.g., in income, education, ...) or other social networks
  - Although note that we include interactions of $likes_{it}$ with state-level demographics

An instrumental variable strategy

- This is reassuring, but we might still be worried of the heterogeneity picking up differences across states (e.g., in income, education, ...) or other social networks
    - Although note that we include interactions of $likes_{it}$ with state-level demographics
- Following Müller and Schwarz (2022), we implement an IV design using a shock to early Twitter adoption, i.e. attendance to the SXSW festival in 2007

The main finding is robust to using the SXSW instrument

	OLS			2SLS			2SLS: First stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Small donations						Likes X Twitter use		
Likes X	0.001***	0.001***		0.001***	0.001***	0.001***			
Twitter use	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)			
Likes X			0.001***				0.703***	0.696***	0.522***
$\text{SXSWFollowers}^{2007}$			(0.000)				(0.061)	(0.120)	(0.107)
Likes X					0.000	0.000		0.010	0.128
$\text{SXSWFollowers}^{2006}$					(0.000)	(0.000)		(0.137)	(0.092)
Pair X Month FE	X	X	X	X	X	X	X	X	X
ID X Date FE	X	X	X	X	X	X	X	X	X
State X Date FE	X	X	X	X	X	X	X	X	X
Controls		X				X			X
Obs. (million)	16.6	16.6	16.6	16.6	16.6	16.6	16.6	16.6	16.6
# Clusters: *MOC*	506	506	506	506	506	506	506	506	506
# Clusters: *State*	49	49	49	49	49	49	49	49	49
F Stat							130.686	33.803	23.740

Conclusions

Conclusion

- We find that attention on Twitter increases contributions from small donors, showing that Twitter can be an effective technology to raise donations

Conclusion

- We find that attention on Twitter increases contributions from small donors, showing that Twitter can be an effective technology to raise donations
- But because returns are highly concentrated, this does not happen for everyone: only few MOCs are able to harness attention

Conclusion

- We find that attention on Twitter increases contributions from small donors, showing that Twitter can be an effective technology to raise donations
- But because returns are highly concentrated, this does not happen for everyone: only few MOCs are able to harness attention
- Still many interesting open questions on how whether these forces might be sufficient to create perverse incentives on messaging

Thank you!

ornaghi@hertie-school.org