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

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The age of attention

- Social media represents a major structural change in mass communication
- Relative to the concentrated, top-down broadcast model of newspapers or TV, social media is multi-channel communication technology due to low barriers to entry
  - Massive amounts of information are produced and shared on social media daily
- As a result, attention has become a scarce, precious, and contested resource
  - Politics is no exception
  - '*Attention, not money, is now the fuel of American politics*' Ezra Klein
- **Question**: how does the market for attention on social media function?

What we do

- We investigate this question by studying whether and how the attention that US Members of Congress (MOCs) receive on Twitter translates into campaign donations
  - Focus on 116th Congress (2019-2020)
  - Campaign donations $\rightarrow$ financial metric to estimate returns to attention
- We estimate donations-attention relationship using two empirical approaches
  1. We use a MOC-by-date panel to estimate relationship within-MOC/month
  2. We use MOC-by-county-by-month panel to test whether effect is indeed driven by areas with higher Twitter usage and implement IV strategy
- We use these designs to characterize returns to attention
  - How do returns vary with the level of attention? Is this a winner-takes-all or distributed market? What types of messages are better at generating returns?

What we find

- Twitter likes are **positively related** to donations, but average magnitude is modest
- This masks substantial heterogeneity, as **returns are highly skewed**
  - Twitter is an effective technology to increase donations, but only for those who are able to garner high levels of attention
  - The effect is highly robust and goes beyond the news cycle
- Result is driven by high-Twitter-usage counties and robust to using IV strategy

Our contributions

1. We contribute to growing literature focused on understanding the effects of social media on political outcomes such as participation, mobilization, etc.
   Bond et al. 2012, Allcott et al. 2020, Fujiwara et al. Forthcoming, Enikopolov et al. 2020, Bessone et al. 2022 [...]
   - Focus on specific political behavior: decision to donate to a campaign
2. Political economy literature on the determinants of campaign contributions
   Gerber 2004, Snyder 1990, Dawood 2015, Petrova et al. 2021, Bouton et al. 2024, Bouton et al. 2024
   - Find suggestive evidence of expressive motives being behind decision to donate to political campaign, but that pull factors also matter
   - Relative to Petrova et al. (2021), focus on social media platform at maturity, where competition for attention is a first-order constraint, with different winners and losers
3. Literature on superstar markets Rosen 1981, Celerier and Vallee 2019, Koening 2023
   - Market for attention on Twitter shows hallmarks of superstar markets

Data & Descriptives

Data

- Twitter activity of MOCs in 116th Congress (2019-2020)
  - Text of all tweets and the respective metrics (likes, retweets, replies) for 501 MOCs
  - 1.1 million Congressional tweets over this period
  - Information is aggregated at the day-by-MOC level
- Individual campaign contributions from public FEC dataset
  - Includes direct and indirect (i.e., through conduits) donations for individuals who donate more than $200 over the electoral cycle
  - Focus on donations <$1000 (37% of donations, 94% of donors)
- In addition to...
  - MOCs' mentions in traditional media from Internet Archive (cable news), NYTimes API (NYTimes), newslibrary.com (local newspapers)
  - MOCs' IRL activities such as visits and Congressional speeches
  - County controls, Twitter users, and SXSW followers from Müller and Schwarz (2023)

Descriptive statistics

	Mean	SD	Median
Twitter			
Likes	2990.811	24843.474	31.000
Likes $>$ 2000	0.092	0.289	0.000
Replies	319.470	2265.853	6.000
Retweets	709.071	5017.033	9.000
Tweets	2.931	4.135	2.000
Other Shocks to Attention			
Cable news mentions $>$ 0	0.109	0.312	0.000
Mentioned on cable news & Top 10% Twitter	0.043	0.203	0.000
Mentioned in the NYT	0.011	0.102	0.000
Mentioned in the NYT & Top 10% Twitter	0.008	0.089	0.000
Mentioned in local newspapers	0.064	0.245	0.000
Mentioned in local newspapers & Top 10% Twitter	0.023	0.151	0.000
Donations			
All donations	3273.546	22723.499	0.000
Small donations	1219.040	11788.448	0.000
Small donations, if donations $>$ 0	2725.097	17508.605	525.000
All donors	15.946	186.223	0.000
Small donors	15.026	183.437	0.000
Small donors, if donors $>$ 0	33.590	273.126	4.000

Returns to Attention

Baseline specification

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

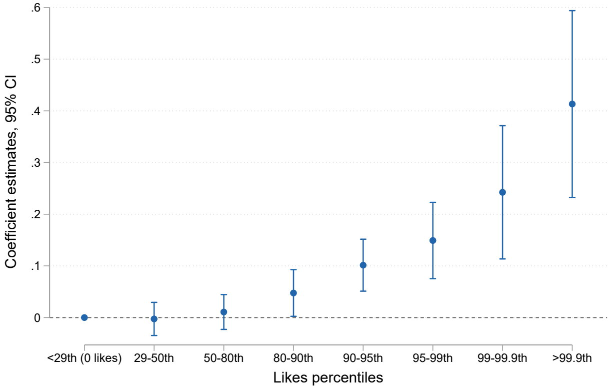
$$y_{it} = \beta likes_{it} + \alpha_{im(t)} + \tau_{p(i)t} + \epsilon_{it}$$

  - y_{it} is the log+1 of the aggregate small contribution to MOC i on day t
  - $likes_{it}$ is the log+1 total likes of MOC i on day t
  - $\alpha_{im(t)}$ are MOC by month FEs $\rightarrow$ ensure we only exploit within-person variation in donations in periods where levels are comparable
  - $\tau_{p(i)t}$ are party by day FEs $\rightarrow$ allow parties to be exposed to different shocks
  - Standard errors clustered at the MOC level

There are positive returns to attention on social media

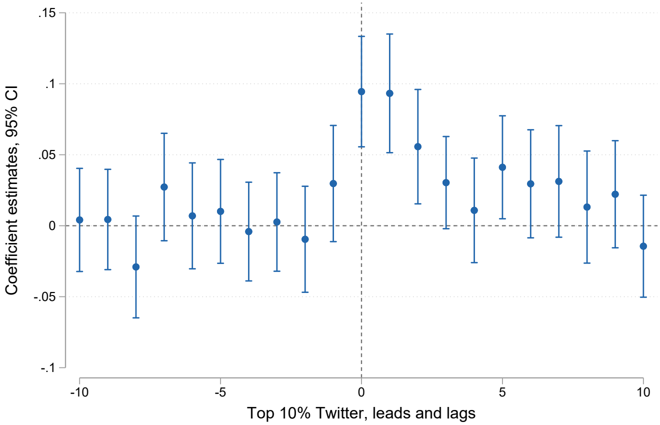
	Small donations						
	Log + 1					Dummy	Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Likes + 1)	0.352***	0.039***	0.042***	0.011***			
	(0.024)	(0.006)	(0.006)	(0.003)			
Top 10% Twitter					0.094***	0.006*	0.053***
					(0.019)	(0.003)	(0.014)
Date FE	X	X					
MOC FE		X	X				
Date-by-party FE			X	X	X	X	X
MOC-by-month FE				X	X	X	X
Observations	335670	335670	335670	335670	335670	335670	149200
MOCs (clusters)	501	501	501	501	501	501	496
Mean dep. variable	2.799	2.799	2.799	2.799	2.799	0.447	6.247

Returns to attention are highly skewed over the distribution



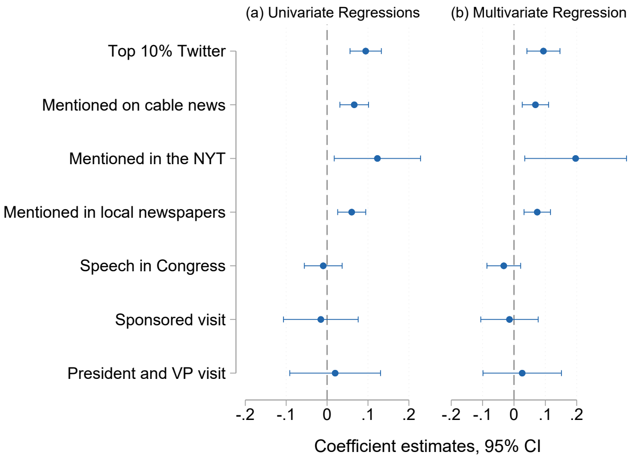
- Not just mechanical: elasticity of donations to likes is higher for viral tweets [more]

Estimating leads and lags shows minimal anticipation effects



- Effect of going viral lasts around three days, and dissipates afterwards

The attention shock goes beyond the news cycle



- These patterns suggest segmentation of the audience across media markets [more]

What about spillovers?

	Top 10% Twitter				Likes	Donations
	(1)	(2)	(3)	(4)	(5)	(6)
Number of viral tweets, weighted	-0.052***			-0.052***	-0.163***	-0.008
	(0.004)			(0.004)	(0.037)	(0.018)
Number of viral tweets, same ideology		-0.001**		-0.001**	0.005	0.004
		(0.001)		(0.001)	(0.006)	(0.005)
Number of viral tweets, same state			-0.002**	0.001	-0.003	0.004
			(0.001)	(0.001)	(0.010)	(0.007)
Top 10% Twitter						0.090***
						(0.020)
Date-by-party FE	X	X	X	X	X	X
MOC-by-month FE	X	X	X	X	X	X
Observations	335000	335000	335000	335000	335000	335000
MOCs (clusters)	500	500	500	500	500	500
Mean dep. variable	0.100	0.100	0.100	0.100	3.479	2.802

- Attention on Twitter is limited, but no spillovers in donations

No evidence of harvesting

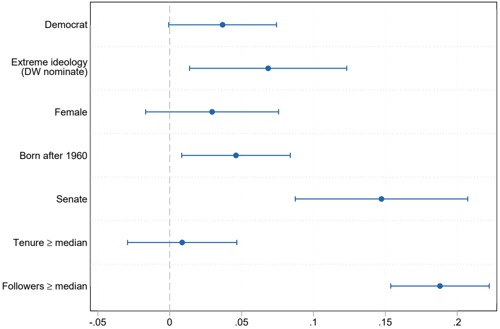
	Small donations					
	Day of	Week after	Month after	Day of	Week after	Month after
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Likes + 1)	0.011***	0.004***	0.000			
	(0.003)	(0.002)	(0.001)			
Top 10% Twitter				0.098***	0.027**	-0.010
				(0.020)	(0.011)	(0.008)
MOC-by-month FE	X	X	X	X	X	X
Date-by-party FE	X	X	X	X	X	X
Observations	320139	320139	320139	320139	320139	320139
MOCs (clusters)	501	501	501	501	501	501
Mean dep. variable	2.723	6.312	7.498	2.723	6.312	7.498

- Twitter attention is not just shifting donations across time (at least in the short run)

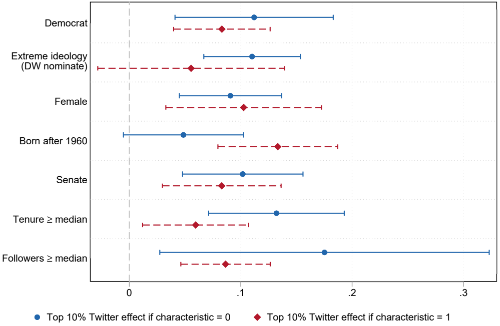
Making sense of the magnitudes

- A viral day increases donations by 5.3% if we only consider contemporaneous effect and 12% if we consider the cumulative effect over three days
  - This is equivalent to $144 (one day) and $327 (three days) more donations
- Because top 5 MOCs by number of likes go viral 605 days on average (relative to 31 days for those outside the top 50), they earn additional $83k to $202k on Twitter
  - This corresponds to 10% to 25% higher overall donations over Congressional cycle
- The persuasion rate is ∼2.6%, slightly larger to that of opening a Twitter account (Petrova et al. (2021)) and of political ads (Spenkuch and Toniatti (2018))

MOCs' characteristics matter, but returns not heterogeneous



(a) Attention and MOC Characteristics

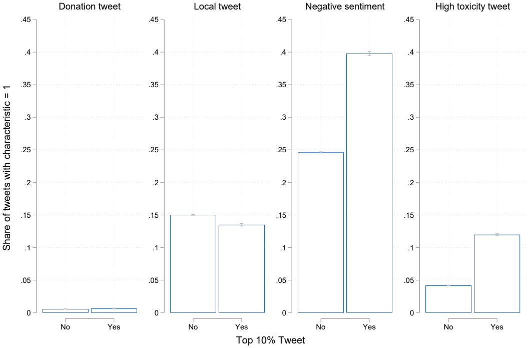


(b) Heterogeneity by MOC Characteristics

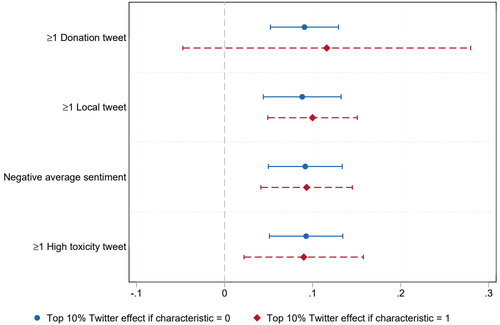
Perverse incentives?

- MOC characteristics influence donations through the probability of going viral
  - Instead, conditional on going viral, returns are not heterogeneous
- Because differences in probability of going viral are generally small, these differences translate into small sums on average
  - MOCs with extreme ideology earn an additional $6k-$16k through Twitter
- But if returns on Twitter are concentrated, we need to move beyond the average
  - Because big winners are more likely to be ideologically extreme, tournament-style dynamics might still create incentives to take-up more extreme positions

Returns to attention are not heterogeneous by tweet content



(a) Attention and Tweet Content



(b) Heterogeneity by Tweet Content

Robustness checks

- Alternative measures of attention and donations do not impact the results [more]
- Findings are robust to functional form and using log+1 parametrization [more]
- Similar leads and lags pattern for different parametrizations and samples [more]

Geography-Based Design

Moving towards causality

- Our preferred specification is restrictive, but the donation-likes relationship might still be driven by MOC-specific unobservable shocks
  - There could be attention shocks that are not well proxied by media mentions
  - Attention could be a by-product of MOCs' campaigning efforts
- To address these possibilities, we develop a geography-based design introducing cross-sectional variation in Twitter usage at the county level
  - Tests whether the increase in donation comes precisely from those counties in which Twitter is more prominent (namely, counties with a higher number of Twitter users)

Baseline specification for geography-based analysis

- We estimate the following specification using a MOC-by-county-by-month panel:

$$y_{ict} = \beta(likes_{it} \times users_c) + \gamma(likes_{it} \times X_c) + \tau_{it} + \theta_{ct} + \delta_{ic} + \varepsilon_{ict},$$

  - y_{ict} is an indicator if MOC i receives donations from county c in month t
  - $likes_{it}$ is the log+1 total likes received by MOC i in month t
  - $users_c$ is the log+1 number of Twitter users in county c
  - X_c is the county-level controls, including Census region FEs
  - τ_{it} are MOC-by-month FEs; θ_{ct} are county-by-month FEs; δ_{ic} are MOC-by-county FEs
  - Standard errors are clustered at the MOC level

An instrumental variable strategy

- This is akin to a shift-share design, where Twitter usage gives us the county-level exposure to the aggregate shock of MOC-specific attention
  - Main concern: Twitter usage might be correlated with other factors that drive the effect of MOC attention exposure on donations
- Following Müller and Schwarz (2023), we implement an IV design using a shock to early Twitter adoption, i.e. attendance to the SXSW festival in 2007
  - If early adoption of social media platform displays persistence, location of Twitter's early adopters at SXSW can provide instrument for Twitter usage today
- Identification requires 2007 SXSW followers to be uncorrelated with the error terms
  - In other words, counties more or less exposed to MOC attention on Twitter, as captured by the variation in Twitter usage driven by the number of SXSW followers in 2007, would have experienced similar changes in MOC-specific donations

Higher-Twitter usage counties are more responsive to virality

	Pr(Any Small Donation)						Likes X Twitter users	
	OLS				2SLS		First Stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Likes + 1)*Log(Twitter Users + 1)	0.0006***	0.0005***			0.0015***	0.0018***		
	(0.0001)	(0.0001)			(0.0003)	(0.0005)		
Log(Likes + 1)*Log(Twitter Users SXSW07 + 1)			0.0008***	0.0009***			0.5596***	0.5177***
			(0.0002)	(0.0003)			(0.0597)	(0.0657)
Log(Likes + 1)*Log(Twitter Users pre06 + 1)				-0.0002		-0.0004		0.1104
				(0.0004)		(0.0005)		(0.1065)
MOC-by-Month Fixed Effects	X	X	X	X	X	X	X	X
County-by-Month Fixed Effects	X	X	X	X	X	X	X	X
MOC-by-County Fixed Effects	X	X	X	X	X	X	X	X
Basic Controls	X	X	X	X	X	X	X	X
Extended Controls		X	X	X	X	X	X	X
Observations	34,135,134	34,135,134	34,135,134	34,135,134	34,135,134	34,135,134	34,135,134	34,135,134
Counties (clusters)	3097	3097	3097	3097	3097	3097	3097	3097
MOCs	501	501	501	501	501	501	501	501
F-statistic							87.842	62.191

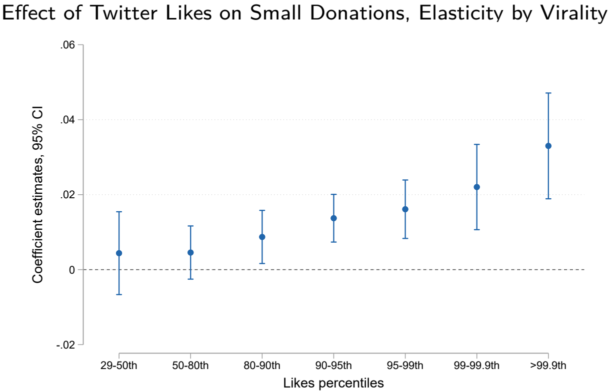
Conclusions

Conclusion

- Twitter can be an effective technology to raise donations, but not for everyone
  - Average returns are small in magnitude
  - But this masks substantial heterogeneity, as returns are highly skewed
- Levels of concentration are similar to traditional media, but because "winners" across platforms are different, social might still widen the playing field [more]

Thank you!

Elasticity also increase with virality



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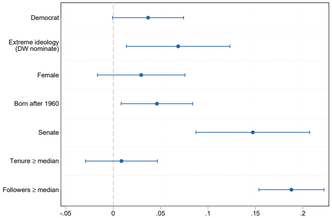
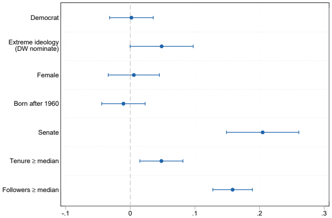
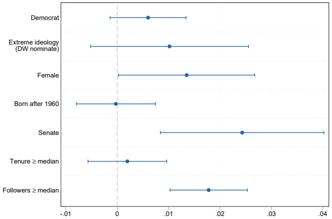
Who goes viral?



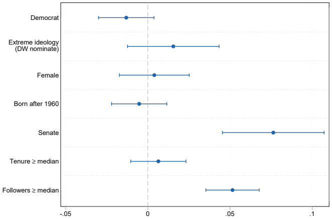
(a) Twitter



(b) Cable news



(c) NYTimes



(d) Local newspapers

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Robustness to variable definitions

	Donations				
	Small			All	Conduit
	(1)	(2)	(3)	(4)	(5)
Replies	0.018***				
	(0.004)				
Retweets		0.016***			
		(0.003)			
Quotes			0.024***		
			(0.005)		
Log(Likes + 1)				0.013***	0.010***
				(0.003)	(0.003)
Date-by-party FE	X	X	X	X	X
MOC-by-month FE	X	X	X	X	X
Observations	335670	335670	335670	335670	335670
MOCs (clusters)	501	501	501	501	501
Mean dep. variable	2.799	2.799	2.799	3.447	2.102

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Robustness to variable definitions

	Small donations				
	Log + 1	$\mathbb{1}(> \$1k)$	$\mathbb{1}(> \$5k)$	Log	Linear
	(1)	(2)	(3)	(4)	(5)
Log(Likes + 1)	0.011***				
	(0.003)				
Top 10% Twitter		0.017***	0.010***		
		(0.004)	(0.002)		
Log likes				0.013***	
				(0.003)	
Likes					0.003**
					(0.001)
Date-by-party FE	X	X	X	X	X
MOC-by-month FE	X	X	X	X	X
Observations	335670	335670	335670	119817	335670
MOCs (clusters)	501	501	501	486	501
Mean dep. variable	2.799	0.154	0.039	6.320	1219.040

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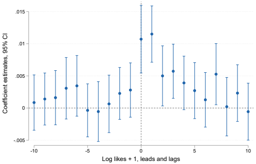
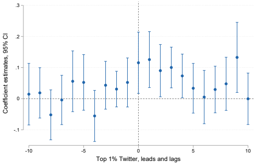
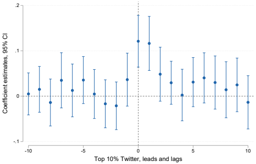
Robustness of the timing of the effect



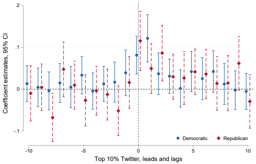
(a) Log 1+Likes



(b) Top 1% Likes



(c) 2019 Only



(d) By Party

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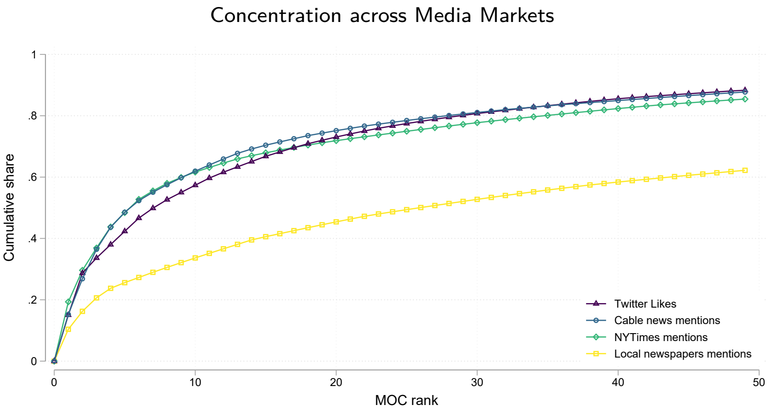
Twitter and traditional media are similarly concentrated



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