The Returns to Viral Media:

The Case of US Campaign Contributions*

Johannes Böken, University of Warwick

Mirko Draca, University of Warwick

Nicola Mastrorocco, University of Bologna

Arianna Ornaghi, Hertie School

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Abstract

Social media has changed the structure of mass communication. In this paper we explore its role in influencing political donations. Using a daily dataset of campaign contributions and Twitter activity for US Members of Congress 2019-2020, we find that attention on Twitter (as measured by likes) is positively correlated with the amount of daily small donations received. However, this is not true for everybody: the impact on campaign donations is highly skewed, indicating very concentrated returns to attention that are in line with a 'winner-takes-all' market. Our results are confirmed in a geography-based causal design linking member's donations across states.

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*Johannes Böken: johannes.boken@warwick.ac.uk; Mirko Draca: m.draca@warwick.ac.uk; Nicola Mastrorocco: nicola.mastrorocco@unibo.it; Arianna Ornaghi: ornaghi@hertie-school.org. We thank Nathan Canen, Carlo Schwarz, Niko Wolf, and seminar and conference participants at the 2023 NICEP Conference, the 12th CRC TRR 190 Retreat, London Business School, Navarra University, and the IEB Political Economy Workshop.

1 Introduction

Social media represents a major structural change in the nature of mass communication. In contrast to earlier broadcast media technologies such as newspapers, radio, and TV, social media is massively multi-channel due to its low barriers to entry. Any user can set up an information feed and popularize it. As a result, massive amounts of information are produced and shared on social media on a daily basis. This makes attention scarce, which in turn creates fierce competition among content producers to secure popularity, specifically the extreme, network-driven type of popularity known as virality.

In this paper, we study whether attention on social media generates tangible economic returns by investigating the relationship between attention on Twitter and campaign donations to Members of Congress (MOCs) in the United States. We focus on representatives who served in the 116th Congress, which includes the 2-year period leading up to the 2020 election when a record $4 billion was donated to congressional candidates (Federal Election Commission, 2021). Our main finding is that attention on Twitter is positively correlated with donations received, but that the relationship is driven by viral days, highlighting that the returns to attention on Twitter are highly skewed.

Twitter plays a significant role in modern politics by influencing political discourse, mobilizing political movements, and providing a platform for leaders, organizations, and citizens to engage in public discussions. Its real-time access to large audiences and vast potential for interaction make it an essential tool for political campaigns. Petrova et al. (2021) document a positive relationship between the opening of a Twitter account and political donations received by MOCs in the 2009-2014 period, when the platform was still growing. The goal of this paper is different. We aim to characterize not only *if* but also *how* attention on Twitter affects campaign contributions once the technology has reached a saturated stage. The effects at maturity might look different precisely because of the characteristics of this social media platform. On one hand, Twitter offers immediate and free access to a wide audience. But on the other, its networked design crowds out non popular tweets creating an environment where users are constantly competing for attention. Politicians are not an exception to this, which we believe makes studying the market structure of Twitter attention an interesting question.

Technically, the modeling problem that we face in this setting is analogous to the lift problem in advertising, that is, attributing causal links between persuasive messages transmitted to targeted audiences and their resulting financial decisions, in this case the propensity to donate (Aral, 2021). We address this challenge by using different levels of aggregation and types of variation to establish the pattern of linkages between attention on Twitter and political donations. Furthermore, this analysis is also able to show how this link is related to the networked, endogenous feedback mechanisms intrinsic to Twitter, specifically the skewed or viral nature of attention on the platform.

The first empirical approach that we adopt is based on a daily panel of sitting MOCs where we relate the amount of daily donations below $1000 received by an MOC to contemporaneous attention on Twitter, that we proxy using likes. We document a positive correlation between donations and attention. The correlation is highly robust and has a modest magnitude when considered on a within-person basis. However, if we decompose this relationship according to a step-function based on different thresholds of attention, we see that it is driven by activity in the very top of the likes distribution. Specifically, we estimate that appearing in the top 10% of the likes distribution, what we define as going viral, is associated with a 0.6 percentage points increase in the probability of receiving a donation and approximately a 4.7% increase in the amount of donations at the intensive margin. There is no significant association below the 80th percentile of likes and it is in this sense that we can characterize the returns to attention on Twitter as a winner-takes-all market.

Our results show that Twitter is a technology that can be effective for raising donations, but not for everyone. The nature of the platform, with its emphasis on engagement and visibility, tends to amplify the popularity of certain tweets over others and it is only these viral messages that seem to translate into concrete financial returns. Indeed, we document a crowding out effect of viral days. When looking at two MOCs sharing 20% of their followers, the probability of one of them having a viral day decreases by about 10% if the other MOC is currently going viral and, interestingly, this is not driven by similar ideology or geographic proximity.

We also study *who* and *what* goes viral. We find that that emotionally negative and ideologically polar positions win significant premia in generating likes and achieving virality. However, when looking at the heterogeneous effects of these message characteristics on campaign donations, we find no further effect. That is, negative or ideologically polar tweets do not have intrinsically higher returns beyond their role in simply securing more likes. This suggests that the main channel through which the content of the tweets and the characteristics of the MOCs impact donation is precisely by changing the probability of going viral.

We then exploit our MOC-level daily panel to test the robustness of our analysis. First, we study the timing of the relationship using a specification including leads and lags of viral days. This indicates that the donations-likes relationships is a temporally concentrated one, unfolding mainly over two days with limited evidence of leads. Such leads would be an indicator of systematic reverse causality from donations to likes, for example, cases where donations were used to support offline campaign activity (e.g., rallies) or online advertising which then generated likes.[1] This exercise also provides information on the timing of the effect: the impact of going viral is relatively short-lived and fades after three days. Second, we look at another information channel that could be correlated with attention on Twitter: cable news. Attention on Twitter could be proxying for an MOC's general presence in the news cycle, making the interpretation of our results subject to omitted variable bias concerns. We therefore control for MOC-specific coverage measures derived from cable news transcripts. The donations-likes relationship is robust to this control and a descriptive analysis indicates that there are distinct profiles to attention received via Twitter versus cable news. Notably, we find that the magnitude of effects for being in the top 10% of the respective distributions across the two information channels is very similar.

The second modeling strategy that we adopt is based on a daily state-by-MOC panel. This allows us to implement a geography-based design that tests whether the increase in donations that MOCs experience when they gain more attention on Twitter is indeed driven by states with higher cross-

[1] In addition and reassuringly, when analyzing the content of the tweets we do not find evidence that our findings can be explained by MOCs using Twitter to directly solicit donations.

sectional rates of Twitter usage. This has the additional advantage of allowing us to include a much richer set of fixed effects (namely, MOC-by-date fixed effects), that take into account many of the concerns highlighted thus far. For identification, following Müller and Schwarz (2023), we use the shock associated with the 2007 South by Southwest (SXSW) festival as an instrumental variable (IV) for Twitter usage across areas. The 2007 SXSW festival was a critical diffusion event in the history of Twitter that shaped the geographical pattern of the network's usage rates in long run. Both the OLS and the IV show that in days in which MOCs receive more attention on Twitter, they experience more donations from states with higher Twitter usage. The IV estimates are in line with the OLS versions and we calculate magnitudes that are comparable to those seen in our daily MOC-panel estimates.

This paper contributes to three main literatures. First and foremost, we contribute to the growing literature studying the effects of social media on political outcomes, including political participation (Bond et al., 2012), voting (Fujiwara et al., Forthcoming), polarization (Allcott et al., 2020), mobilization (Enikolopov et al., 2020), and, more recently, politicians' behavior (Bessone et al., 2022; Schöll et al., 2023). While we only mention a handful of examples here, we refer to Zhuravskaya et al. (2020) and Lorenz-Spreen et al. (2023) for two recent systematic reviews of work in this area. In this paper, we focus on a different political behavior: campaign donations. Closely related to our work is Petrova et al. (2021), who show that when politicians running for Congress in the United States in the 2009-2014 period open a Twitter account, they experience a significant increase in the campaign contributions they receive. Rather than studying the effect of taking up this new communication technology, we focus here on how attention on social media impacts donations at a more mature stage of the market: when all politicians have a Twitter account with a large number of followers and the overall user base has reached a plateau.[2] In such a market, as we document, it is not being on the platform per se that matters, but how much attention one is able to get. In line with this, we show that who benefits on the platform is different at different stages. While new entrants are particularly able to benefit in the earlier period (Petrova et al., 2021),

[2]The number of monthly active Twitter users started plateauing around 66 to 69 millions in 2016 (Statista, 2023).

as Twitter emerges as a novel communication channel, by the end of the 2010s only the people who go viral very regularly are able to harness sufficient attention to make a difference in terms of donations. Related to our work is also Rotesi (2023), who looks at the effect of Twitter penetration on political participation and donations around US presidential elections in 2008, 2012, 2016. In addition to focusing on donations given by citizens rather than donations received by politicians, this paper also looks at an earlier period when adoption was still growing.

In addition, we contribute to the literature in economics and political science on the determinants of US campaign contributions and their effect on electoral outcomes (Gerber, 2004; Snyder Jr, 1990; Fouirnaies and Hall, 2014; Fouirnaies and Fowler, 2022, see Dawood (2015) for an extensive review). While earlier work in this area focused on large donors (Heerwig, 2016; Rhodes et al., 2018; Teso, 2022) researchers have recently shifted their attention to small donors, who are becoming more and more relevant in terms of number and volume of donations, but might display different behavior and motives (Alvarez et al., 2020; Bouton et al., 2022; Culberson et al., 2019)). Although the focus on our paper is on social media, our results provide interesting evidence as to why individuals engage in small donations. The fact that short-term shocks to attention on social media are sufficient to impact donations is highly suggestive of expressive (rather than strategic) motives being behind the decision to send a monetary contribution to a campaign, but also that pull factors matter for donation decisions, in line with what Bouton et al. (2022) also find.[3]

Finally, we contribute to the literature on superstar markets, as initiated by Rosen (1981) and explored in contributions such as Célérier and Vallée (2019), Gabaix and Landier (2008), Koenig (2023), Krueger (2005) and Terviö (2009). The prominence of network-based sharing in the design of the Twitter platform fits the characteristics of 'scale related technical change' (Koenig, 2023); and the skewed pattern of attention and resulting contributions that we observe in our data clearly reflects the structure of a typical superstar market setting. Adding even further, the winner-takes-all nature of the platform is also evidenced by our crowding out results. But our findings are also

[3] Bouton et al. (2022) first find that the number of small donors and their total contributions have been growing over the period 2005-2020. Second, they also show who are these small donors and when they are more likely do donate. In particular, they find that pull factors such as TV ads affect their behavior.

notable for how meager the prize is for the winners. At the mean, the typical MOC ranked 6-50 in terms of attention only raises an additional $27024 (3% of the MOC mean) as a result of their Twitter activity over a two year period and this rises to only $73,517 (9%) for most viral Top 5 MOCs. Even allowing for the fact that a Twitter account is a free resource with (notionally) low running costs, the financial return that we observe is strikingly low. Notably, the focus of our study is the short-run, within-person margin related to daily changes in attention. Given the pervasive attention paid to the platform by MOCs and the general political class, our results therefore indicate that the returns to Twitter activity might lie elsewhere in, for example, higher professional profiles, long-term fundraising, 'ego rents' from personal attention, or the capacity to mobilize highly partisan sub-groups.

The remainder of the paper proceed as follows. Section 2 describes the data. Section 3 provides information about the background, and descriptive characterization of attention on Twitter. Section 4 reports our empirical approach and our main results, while Section 5 describes the analysis that also exploits geographic variation. We conclude in Section 6.

2 Data

2.1 Data Sources

We combine data from various sources described below. For our first analysis we build a daily panel that combines MOCs' activity and popularity on Twitter with detailed data on political donations and additional measures of coverage by traditional media. For our second analysis, we further distinguish donations by geography, adding data on donors' location reported by the FEC and local Twitter penetration obtained from Müller and Schwarz (2023).

Twitter Data. Our main dataset is based on the social media messages (tweets) of sitting MOCs during the 116th Congress between January 2019 and October 2020. We collect the tweets of 533 MOCs across their personal, congressional and campaign accounts (since our data collection and analysis were conducted in early 2021, we lack information on a small number of MOCs who exited

Congress after the November 2020 election and retired their accounts or were otherwise suspended from the platform). In addition, we drop 25 individuals who did not record individual contributions during the study period, 2 non-voting delegates, and 3 MOCs who did not serve a full term. The resulting database comprises over 1.1 million Congressional tweets from 501 different MOCs. In addition to the text of the tweets, we collect the following standard metrics: likes (click-based expressions of approval), retweets (forwarding of messages to individual's followers), and replies (messages sent in response to a tweet). We also collect the Twitter IDs of each MOC's followers to compute the overlap of followers across different MOCs.[4]

FEC Contributions. Our data on campaign contributions comes from the public FEC database on donations by individuals. We include all direct and indirect donations going to a candidate's committee. This includes, in particular, donations that go through conduits.[5] Additional information includes the donation amount, date of receipt, the sender's location (ZIP code), and whether the donation went directly to a candidate's campaign or came through a conduit. Following Petrova et al. (2021), we focus on small donations, which we define as donations smaller than \$1000. This is motivated by large donors probably having different motives and being unlikely to be affected by social media. This restriction thus implies that we focus on the persuasion of individual donors without over-weighting high-value donations, but we show robustness of our results to other definitions in Section 4.5. Overall, small donations under \$1000 account for 37% of contributions from individuals, and 94% of donors in our data.

Cable News Coverage. To measure attention from other media sources, we collect daily, MOC-specific cable news coverage. We obtain measures of coverage using the transcripts of cable news programs of three major cable channels (CNN, FNC, MSNBC) available from the Internet Archive. For each MOC, we count the number of mentions of their full name ("Nancy Pelosi") or their title and last name ("Representative Pelosi") and define our measure of cable news coverage as the sum

[4]Due to a technical glitch in the data collection, we do not have the followers of Representative Seth Moulton.

[5]The FEC's website defines conduits as follows: "Anyone who receives and forwards an earmarked contribution to a candidate or a candidate's committee is considered a conduit or intermediary." Conduits include online fundraising platforms such as ActBlue and WinRed, that have become increasingly relevant as vehicles to collect small donations in recent years (Bouton et al. (2022)).

across the three channels.

Local Twitter Usage. We obtain data on Twitter usage and early Twitter adoption from Müller and Schwarz (2023). Twitter users are measured by the number of unique users tweeting from a given location in a 75% sample of all geo-tagged tweets from the US between 2014 and 2015 (Kinder-Kurlanda et al., 2017). To measure early adoption of Twitter, we use the number of local users following the SXSW Twitter account (@SXSW) who joined in March 2007, in the wake of the 2007 SXSW festival. Furthermore, we use data on SXSW followers who joined before 2007 as an additional control and placebo check for validation. For our main analysis, we aggregate the data at the state level. Additional details, validation, and discussion can be found in Müller and Schwarz (2023) and Fujiwara et al. (Forthcoming).

Other Data. We obtain information on MOCs' demographics and tenure from the @unitedstates github repository and the Library of Congress. To measure MOCs' ideology, we use the first dimension of the voteview DW-nominate score (Lewis and Sonnet, 2022), which captures the traditional liberal-conservative spectrum in economic matters. We obtain county-level socioeconomic information from the USDA rural atlas and vote shares in presidential elections from the MIT Election Data and Science Lab (2018). We also use data from the 2020 wave of the American National Election Studies (American National Election Studies, 2021), a representative survey of eligible voters.

2.2 Descriptive Statistics

Table 1 reports summary statistics for our main dataset. It covers 501 MOCs over 670 days from January 1st, 2019 to October 31st, 2020. We see that MOCs receive on average just under 3000 likes per day across all of their accounts, although these numbers are very skewed: the median number of daily likes is 31 and only 9% of MOC-days yield more than 2000 likes. MOCs' accounts send on average almost 3 tweets per day and receive over 320 replies and 710 retweets. Cable news attention is similarly skewed to Twitter popularity. While MOCs are mentioned on average 1.4 times per day on cable news across channels, on an average day only 11% are mentioned at all. Out

Table 1: Descriptive Statistics

	Mean	SD	Median
Twitter			
Likes	2990.81	24843.47	31.00
Likes > 2000	0.09	0.29	0.00
Replies	319.47	2265.85	6.00
Retweets	709.07	5017.03	9.00
Tweets	2.93	4.13	2.00
Cable news			
Cable news mentions	1.42	15.58	0.00
Cable news mentions > 0	0.11	0.31	0.00
Cable news mentions > 0 & Likes > 2000	0.04	0.20	0.00
Donations			
All donations	3273.55	22723.50	0.00
Small donations	1219.04	11788.45	0.00
Small donations, if donations > 0	2725.10	17508.60	525.00
All Donors	15.95	186.22	0.00
Small donors	15.03	183.44	0.00
Small donors, if donors > 0	33.59	273.13	4.00

This table presents summary statistics on daily Twitter activity, cable news coverage, and campaign donations received for the 501 MOCs part of our sample. The dataset is an MOC-by-date panel.

of those MOCs mentioned by cable news, 37% also receive more than 2000 likes on the same day (or 4% of the sample overall). This means that there is some overlap between Twitter and cable news, but it is not extreme.

Contributions also follow a skewed pattern and are very sparse. MOCs in our sample receive over $1200 per day in small donations from 15 distinct donors but no donations at the median. Conditioning on receiving at least one donation, the average amount of small donations received is higher at $2725 per day from 33 donors. Note that our definition of small donors excludes disproportionately large donations. Including large donors adds on average less than one additional donor (6%) but increases the average donation by over $2000 (170%) relative to the small-donation sample.

3 Background

3.1 Overlap Between Twitter Usage and the Propensity to Donate

The potential influence of Twitter on political donations is naturally a function of the size and composition of its reach. Commentators such as Klein (2022) characterize Twitter as the primary social network for elite professionals across knowledge-based industries.[6] Indeed, using data from the 2020 wave of ANES (a representative survey of eligible voters), we find that Twitter users have higher incomes, are more urban, are more educated, and are more likely to identify with the Democratic party than the population average (Appendix Table A1).[7] Most importantly in our setting, Twitter users are more likely to donate to political causes, in particular to individual candidates; occasional Twitter users are 13% more likely and daily Twitter users are 57% more likely to have donated to a candidate in 2020 than the population average. This effect is not driven by other demographics: a simple linear probability model predicts that occasional Twitter users are 32% more likely and daily Twitter users are 74% more likely to have donated to a candidate than the sample mean, holding income, education, location, and party affiliation fixed.[8] This data indicates that the Twitter network provides politicians a direct channel to a very active, politically engaged audience.

3.2 The Characteristics of Twitter Attention and Political Donations

Twitter is in theory very accessible and the first barrier to entry, the creation of an account, seems low. However, obtaining and maintaining a large number of active followers is challenging because

[6] As Klein (2022) notes: 'Twitter might have a smaller user base than Facebook, Instagram and even Snapchat, but it shapes the dominant narratives in key industries like politics, media, finance and technology more than any other platform. Attention–particularly that of elite leaders in these industries–is a valuable resource, one that Twitter manages and trades in.'

[7] This is in line with findings from a Pew Research Center survey (Wojcik and Hughes (2019)).

[8] We run an OLS regression of an indicator equal to one if an individual contributed to a candidate on indicator variables for occasional and daily Twitter use and controls for income, education, location, political leaning (details on the variables are in the notes of Appendix Table A1). The estimated coefficients of those indicators are 0.051 and 0.118 (both significant at $p<0.001$ with robust SEs); the omitted category is no reported Twitter use. The sample mean of the outcome variable is 0.1597.

Twitter, like many other (online) social networks, exhibits high degrees of concentration, positive degree assortativity, and ideological homophily (Mislove et al., 2007; Antonakaki et al., 2021; Zhuravskaya et al., 2020). As shown in Appendix Figure A1, the distribution of likes on Twitter between MOCs is very concentrated, and the degree of concentration is comparable to traditional cable news: the 25 most popular MOCs on Twitter and cable news receive 77% of likes and 78% of mentions and the top 50 MOCs receive 88% of likes and 88% of mentions. There is some overlap in Twitter and cable news popularity, but it is not extreme: out of the top 50 MOCs by Twitter likes, 56% are also in the top 50 by cable news mentions.

3.3 Who and What Goes Viral?

Twitter is a platform where information spreads rapidly and widely. Investigating what goes viral is therefore helpful for understanding the mechanisms and patterns of information dissemination. This can be examined in terms of characteristics of the sender as well as the content of tweets. In this section, we establish patterns regarding the drivers of Twitter attention. This is not only interesting per se, but will also assist us in studying the heterogeneity of our results across these characteristics.

We begin by considering *who* goes viral, by estimating the correlation between being in the top 10% of the likes distribution and different MOC characteristics. Appendix Figure A2 reveals several interesting patterns. First, looking at ideology, we can see that MOCs from the Democratic party are more likely to go viral. This is unsurprising given the political leaning of the platform's user base. Regardless of party, MOCs at the extremes of the ideological distribution (defined as being in the bottom and top decile in the distribution of the DW nominate score) also get more attention on the platform. Second, as far as demographic characteristics are concerned, female MOCs do not appear to receive differential attention of the platform, while younger MOCs do. Third, we see that MOCs serving in the Senate receive more attention on Twitter but that having a longer tenure has no effect.[9] Finally, as we would mechanically expect, MOCs with more followers are significantly

[9]That MOCs serving in the Senate are more likely to go viral might be surprising. However, they also tend to have a higher number of followers, which might explain the pattern we see here. In line with this, running a horse race between the two characteristics cuts the effect of being in the Senate by three and leaves it not statistically significant at

more likely to go viral.

We then focus on *what* goes viral by looking at the content of the tweets. Appendix Figure A3 shows the share of tweets that contain a specific type of content, separately by whether the tweet is in the top 10% of the likes distribution or not. First, we observe that more localized tweets are slightly less likely to be popular. Around 15% of non-viral tweets have a local nature, in that they refer to municipalities in the congressional district of the MOC, versus 13% of viral tweets. Second, using a dictionary-based method (Valence Aware Dictionary for Sentiment Reasoning or VADER), we see that certain types of content resonate more with people, leading to more sharing and engagement. In particular, we show that tweets that go viral are 15 percentage points (60% of the baseline mean) more likely to have negative sentiment than tweets that do not receive substantial attention on the platform. We similarly see that tweets that have a high toxicity score according to Google's Perspective API (i.e., a toxicity score in the top 5% of the distribution, or higher than 0.22) are three times more common among viral than among non-viral tweets.[10] While these results are not surprising to those familiar with the Twitter platform we think they are notable in terms of a) the magnitude of the implied relationship; and b) the potential to create perverse incentives when factored into the capacity to attract donations. Finally, MOCs rarely use Twitter to directly solicit donations: less than 0.5% of tweets include a direct link to a donation platform. This suggests that it is unlikely that the effects we will see will be explained by strategic soliciting behavior on part of the MOCs.

conventional levels.

[10]To put this in perspective, toxicity scores higher than 0.30 are generally considered to be suspect and higher than 0.80 are considered to be hate speech. Perhaps reassuringly, only 174 tweets (our of more than 1.1 millions) have a toxicity score higher than 0.80. As a comparison, 5.6% of tweets were found to meet the threshold in a random sample of English language tweets (Jiménez Durán, 2021).

4 Daily Panel

4.1 Modeling Framework

The first part of our analysis follows a panel structure with daily variation in our variables of interest. In particular, we estimate the following baseline specification:

$$y_{it} = \beta likes_{it} + \alpha_{im(t)} + \tau_{p(i)t} + \epsilon_{it}, \tag{1}$$

where y_{it} is the log+1 of the total amount of contributions below \$1000 received by MOC i on day t; $likes_{it}$ is the log+1 total likes received by MOC i on day t; $\alpha_{im(t)}$ are MOC-by-month fixed effects; $\tau_{p(i)t}$ are date-by-party fixed effects. Standard errors are clustered at the MOC level.

The strength of this specification is that it offers a within-MOC analysis. That is, we control for heterogeneity in both the amount of small donations and the average amount of Twitter attention that an MOC receives on average. The addition of MOC-by-month fixed effects, $\alpha_{im(t)}$, ensures that the within-person comparison occurs in sub-periods where the level of donations is comparable. This is important in our setting as donation levels escalate as the date of the election approaches. The date-by-party fixed effects, $\tau_{p(i)t}$, allow MOCs belonging to different parties to be on different (non-parametric) trends.

The first innovation that we introduce to this specification is to divide the distribution of likes according to different thresholds and estimate a step function. This allows us to measure instances of viral attention, which we define as cases where an MOC-day observation is at or above the 90th percentile in the overall likes distribution. We also use this discretized approach more generally to deal with the many zeroes issue, for example, by formulating extensive margin specifications based on binary variables that flag when donations or attention are positive valued or cross particular thresholds.

The second innovation allows us to investigate the dynamic relationship between virality on Twitter and donations. To do so, we estimate a dynamic version of the baseline equation including leads and lags of our main independent variable, which allows us to track the pattern of donations before and after a viral day. In particular, we estimate the following specification:

$$y_{it} = \sum_{k=1}^{10} \delta_{-k} * \text{Top 10\% Twitter}_{it-k} + \sum_{k=0}^{10} \delta_{+k} * \text{Top 10\% Twitter}_{it+k} + \alpha_{im(t)} + \tau_{p(i)t} + \epsilon_{it}. \quad (2)$$

where Top 10% Twitter$_{it}$ is an indicator for the number of likes that MOC i receives on day t being in the top 10% of the overall likes distribution and all other variables are defined as before. The δ_{-k} and δ_{+k} parameters measure any systematic movements in outcome y_{it} before or after a viral day.

4.2 Daily Panel Results

Table 2 presents our results on the relationship between small donations and likes. Column (1) estimate a specification that only includes date fixed effects. This shows a strong and sizable correlation between the amount of small donations received by an MOC and the MOC's popularity on Twitter. This seems to be driven by variation across MOCs: including MOC fixed effects cuts the effect by a factor of ten (column (2)). Including date-by-party fixed effects, which non-parametrically control for party-specific shocks, does not substantially impact the point estimate (column (3)). We report our preferred specification including month-by-MOC fixed effects in column (4). This highly restrictive specification yields a coefficient of 0.01.

The use of a log+1 transformation complicates the interpretation of the magnitude of our estimates, as the recovered coefficients cannot be interpreted as elasticities (see Chen and Roth, 2023; Mullahy and Norton, 2022). To make progress on this, we begin by discretizing the independent variable, and estimate the effect of being in the top 10% of the likes distribution. Column (5) shows that being in the top 10% of the likes distribution increases log +1 donations by 0.087. Then, we estimate the effect of having a viral day on the extensive and intensive margin separately. Column (6) regresses a 0-1 indicator of receiving any donations on day t on another 0-1 indicator of virality, while column (7) only uses the non-zero variation across MOC-day observations. We find that Twitter virality affects both margins. Being in the top 10% of the likes distribution increases the probability of receiving at least one donation by 0.6 percentage points (1.35% of the baseline mean)

Table 2: Twitter Likes and Small Donations

	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					0.087***	0.006*	0.047***
					(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	149148
MOCs (clusters)	501	501	501	501	501	501	496
Mean dep. variable	2.799	2.799	2.799	2.799	2.799	0.447	6.248

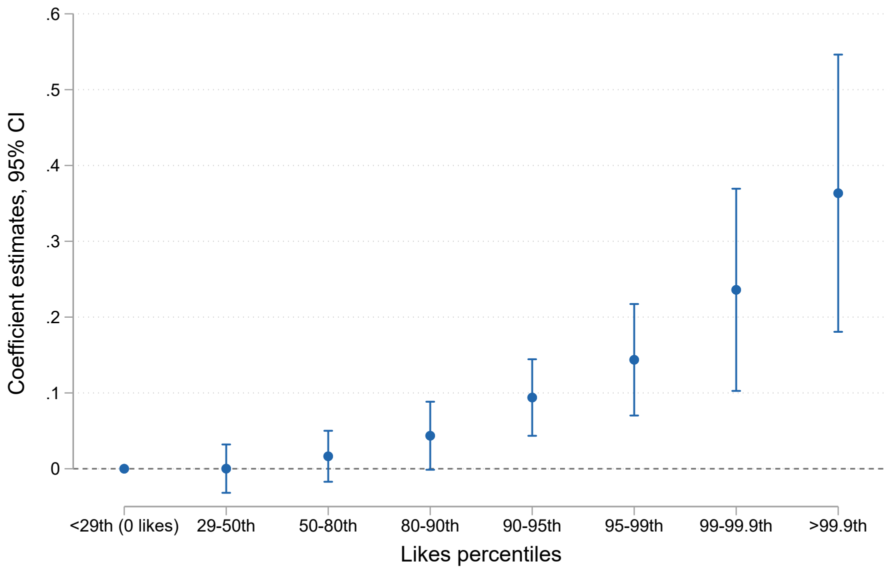
This table shows the relationship between Twitter likes and small donations. In columns (1) to (4), we regress the log+1 of the total amount of donations below $1000 that an MOC receives on a given day on the log+1 of the total Twitter likes the same MOC receives on the same day. Column (1) estimates a pooled specification that includes date fixed effects only, column (2) adds MOC fixed effects, column (3) includes date-by-party fixed effects, and column (4) includes both date-by-party and MOC-by-month fixed effects (equation (1)). Column (5) estimates the same specification as column (4) but using as the independent variable an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more). While using the same specification and the same independent variable, column (6) defines the outcome as an indicator variable equal to one if an MOC receives positive donations and column (7) as the log of the total amount of donations below $1000 that an MOC receives on a given day. In column (7), the sample is conditional on receiving positive donations. Standard errors are clustered at the MOC level.

and, conditional on receiving donations, it increases the amount received by 4.7%.

Viral Impacts. Discretizing the dependent variable helps us understand magnitudes; but it can also be substantively relevant if returns are skewed. We assess the gradient of the basic donations-likes relationship using the step-function approach described in Section 4.1. In particular, Figure 1 shows the relationship between likes on Twitter and small donations for different percentiles of the likes distribution, our measure of virality.

Interestingly, there is no relationship between likes and small donations in the bottom 80% of the likes distribution. However, days with a number of likes in the top 20% of popularity are associated with increased donations and, within this group, the returns to popularity are high. Being in the 90-95th and the 99-99.9th percentile group results in coefficients in the 0.20-0.30 range. These results show how Twitter can be considered a winner-takes-all market. The nature of the platform,

Figure 1: Twitter Likes and Small Donations, by Virality



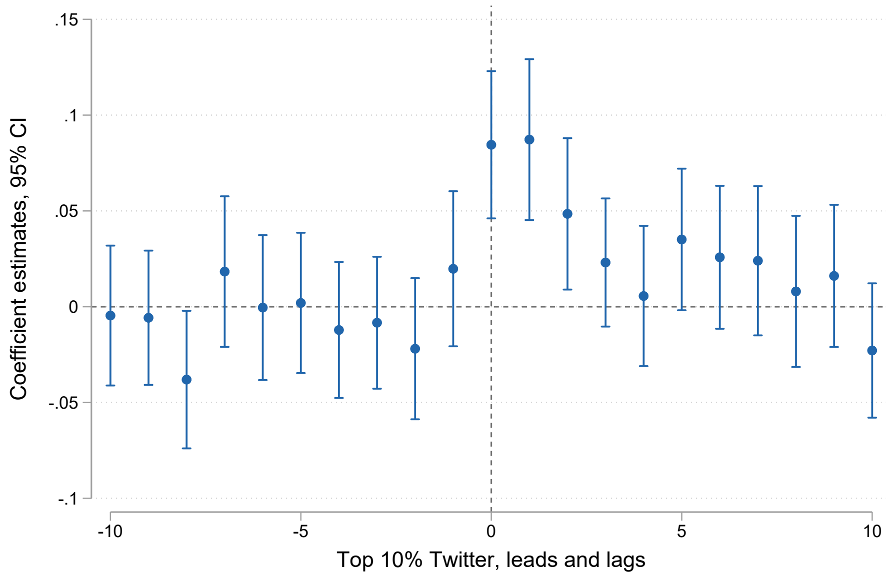
This figure shows the relationship between Twitter likes and small donations, for different levels of virality (i.e., for different percentiles of the likes distribution). In particular, we regress the log+1 of the total amount of donations below $1000 that an MOC receives on a given day on a series of indicators for the number of likes that the MOC receives on the same day being in different percentiles of the likes distribution, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). The omitted category $< 29th$ includes days in the 29th percentile and below (when MOCs receive 0 likes); $29 - 50th$ indicates days in the 51st to 80th percentile (between 32 and 350 likes); $50 - 80th$ indicates days in the 51st to 80th percentile (between 32 and 347 likes); $80 - 90th$ indicates days in the 81st to 90th percentile (between 348 and 1657 likes); $90 - 95th$ indicates days in the 91st to 95th percentile (between 1658 and 7,696 likes); $95 - 99th$ indicates days in the 95th to 99th percentile (between 7,698 and 68,138 likes); $99 - 99.9th$ indicates days in the 100th percentile, excluding the top 0.1% of the distribution (between 68,139 and 320,217 likes); $> 99.9th$ indicates the top 0.1% of the distribution (between 321,134 and 3,808,126 likes). Standard errors are clustered at the MOC level.

with its emphasis on engagement, visibility, and virality, tends to amplify the popularity of certain tweets over others and this in turn seems to translate into concrete financial returns.

Importantly, increasing returns for viral attention is not mechanically explained by viral tweets receiving more likes: we show in Appendix Figure A4 that the coefficient of small donations to the number of likes is almost double for tweets in the highest percentiles of attention. This is in line with the fractal structure of returns found in other empirical studies of superstar markets such as Koenig (2023).

Dynamics. Figure 2 illustrates the dynamic effect by estimating the lag structure for a viral day across 10 leads and lags. This can be interpreted as a test for systematic reverse causality with, for example, donations underwriting activity which would then generates likes. The forward terms are neither individually nor jointly significant in this model. We can reject a joint test that 3 (1) days of forward terms are significant with an F-statistic of 0.86 (p-value=.46) (0.92, p-value=.34).

Figure 2: Twitter Likes and Small Donations, Leads and Lags



This figure shows the dynamic relationship between likes on Twitter and small donations. In particular, we regress the log+1 of the total amount of donations below $1000 that an MOC receives on a given day on ten leads and lags of an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more), date-by-party fixed effects, and MOC-by-month fixed effects (equation (2)). Standard errors are clustered at the MOC level.

We also find a significant difference between the forward and contemporaneous effect of virality (p-value<.05).

Figure 2 also provides information on the timing of the effect. The impact of a viral day is relatively short-lived. After an initial spike, the effect tends to become smaller and fades after three days. Since the leads and lags are included simultaneously, their coefficients can be interpreted as partial effects at k days after an event and we can sum them together to get the total dynamic impact of a viral day shock. Based on Figure 2, there is an overall 0.23 log+1 points increase in donations over the 3 days following a viral day, which is substantially larger than the contemporaneous effect. To the extent that our magnitude calculations focus on the contemporaneous effect only, our elasticity estimate of 4.7% represents a lower bound for the overall effect.

In Appendix Figure A5 we also estimate variations of this basic dynamic model using viral days defined according to different thresholds as well as the continuous measure of likes. These all yield similar leads and lag structures to that seen in Figure 2.

4.3 Cable News

A potential confounding factor in our estimation are events that drive attention towards specific MOCs independently of Twitter, such as political news and events. This attention could direct more small political donations to their campaign, but might also drive Twitter likes, as people start paying more attention to MOCs on social media.[11] Furthermore, cable news coverage could directly affect likes through the direct coverage of tweets or trending topics. To control for this non-Twitter specific newsworthiness, we include cable news coverage as an alternative source of MOC-specific news coverage.

Table 3 presents the results from estimating our main specification with an added control for cable news coverage. We find that both Twitter popularity and cable news coverage are associated with a significant increase in small donations (columns (1) and (2)). Including both variables in column (3) barely changes the individual coefficients. Thus, Twitter likes seem to capture a distinct source of attention beyond cable news reports and their coverage of newsworthy political events.

The extensive margin is the key operating margin for attention via cable news. Only 11% of MOCs are mentioned on cable news on any given day compared to the unbounded, multi-channel nature of potential attention that is feasible on Twitter. Hence, in order to benchmark the effects of Twitter and cable news attention we also estimate our specification in columns (4), (5), and (6) with indicator variables that are equal to one on days in which MOC's are in the respective top deciles of cable news coverage and Twitter likes. We confirm our main findings and show that the returns to viral coverage are very similar in magnitude.

4.4 Discussion

Persuasion Rate. To further interpret the magnitude of our estimates, we calculate persuasion rates (DellaVigna and Gentzkow, 2010). The treatment that we consider is exposure to an MOC's

[11] For example, Benson and Limbocker (2023) suggest that US politicians' cable news appearances increased their campaign contributions.

Table 3: Twitter Likes versus Cable News Mentions

	Log small donations + 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Log likes + 1	0.011***		0.010***			
	(0.003)		(0.003)			
Log cable mentions + 1		0.064***	0.061***			
		(0.014)	(0.014)			
Top 10% Twitter				0.087***		0.082***
				(0.019)		(0.019)
Top 10% TV					0.086***	0.081***
					(0.021)	(0.021)
MOC-by-month FE	X	X	X	X	X	X
Date-by-party FE	X	X	X	X	X	X
Observations	335670	335670	335670	335670	335670	335670
MOCs (clusters)	501	501	501	501	501	501
Mean dep. variable	2.799	2.799	2.799	2.799	2.799	2.799

This table shows the relationship between Twitter likes and small donations, controlling for cable news mentions. In column (1), we regress the log+1 of the total amount of campaign donations below $1000 that an MOC receives on a given day on the log+1 of the number of Twitter likes the MOC receives on the same day, date-by-party fixed effects and MOC-by-month fixed effects (equation (1), see also Table 1 column (4)). Column (2) uses as the independent variable the log+1 of the total number of mentions of the MOC on CNN, FOX NEWS, and MSNBC. Column (3) includes both log+1 likes and log+1 cable news mentions. Column (4) uses as the independent variable an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more), while column (5) uses as the independent variable an indicator for the number of cable news mentions that the MOC receives being in the top 10% of the mentions distribution (2 mentions or more). Column (6) includes both. Standard errors are clustered at the MOC level.

viral tweets, while the behavior is making a donation to the same MOC. Following Fujiwara et al. (Forthcoming), we note that for marginal changes in exposure the persuasion rate can be approximated as $f = \beta * \frac{y}{e(1-y)}$, where β is the estimate of the (conditional) semi-elasticity of viral days on the log number of donors that we estimate from equation (1), e is the share of the population who is on Twitter, and y is the share of the population who donates.[12] Setting $\beta = 0.043$, $e = 0.32$, and $y = 0.16$, we estimate that the persuasion rate is approximately 2.6%. This persuasion rate is lower than the average persuasion rates reported in DellaVigna and Gentzkow (2010)

[12] While the main outcome throughout the paper is the amount of small donations that a candidate receives in a day, persuasion rates are conceptually more appropriate to scale effects on binary behaviors (in this case, donating versus non-donating). This is why we focus on the effect on number of donations in this discussion. To estimate the marginal effect of likes on donors, we estimate equation (1) using the log. number of donors (conditional on receiving at least one donation) as outcome and an indicator for going viral as the independent variable. This gives us a coefficient of 0.043, significant at the 99% level, see Appendix Table A2. This number represents a more accurate estimate of the magnitude, but also a lower bound as it disregards the higher likelihood of receiving donations on high-popularity days. Using the full sample in a Poisson specification or the log 1+x transformation yields similar, slightly larger coefficients.

but slightly larger than the persuasion rate of an MOC opening a Twitter account on donations estimated by Petrova et al. (2021) and the persuasion rate of political advertising on vote share from Spenkuch and Toniatti (2018).[13]

Returns in a Concentrated Market. One key feature of Twitter is that, as we discussed in Section 3.2, attention tends to be highly concentrated. Given the returns we estimate, are these differences stark enough to be consequential for real-world donations? To answer this question, we note that the five MOCs with the largest number of likes over the sample period go viral 605 days on average, those with the 6th to 50th highest number of likes 242 days on average, and everyone else goes viral 31 days on average. According to our quite restrictive specifications, a viral day increases donations by 4.7% on the intensive margin (Table 3, column (5)) which, at a daily mean of $2725 in small donations, corresponds to a marginal effect of $128. Then, a simple back-of-the-envelope calculation tells us that MOCs in positions 1 to 5 (6 to 50) earn an additional $73517 ($27024) over the full sample period from going viral on Twitter. This corresponds to around 9% (3.3%) higher average donations. Importantly, this suggests that Twitter is a technology that can be effective for raising donations, but not for everyone: only very few representatives are able to harness attention on the platform to substantially increase donations from small donors.

Crowding-out of Attention. The concentration in attention can in part be explained by a crowding out effect of viral days. In Table A3, we illustrate how MOCs' likelihood of going viral depends on virality around them. First, we find that users' attention on the platform seems to be limited. We regress an MOC's probability of going viral on the number of other politicians going viral on the same day, weighted by the share of MOC's followers who also follow the other politicians, and find strong and significant negative spillovers (columns (1)). An MOC's probability of having a viral day decreases by 1 percentage point (10% of the baseline mean) if a different MOC who is followed by 20% of the MOC's followers goes viral, or 5.1 percentage points (51% of the baseline mean) if 100% of their followers also follow the other MOC. Note that this is not mechanically driven

[13]Note that this rate represents a lower bound, as it does not account for additional intensive margin effects, no lagged effects on the following days (like in Figure 2) and only considers the short-run effects within a month, due to our fixed effects.

by our relative definition of viral days, as in column (5) we find that the absolute number of likes significantly decreases as well.

We find much weaker spillovers using ideological or geographic proximity. Viral days decrease the probability of going viral for MOCs in the same ideological decile or representing the same state (columns (2) and (3)); however, the effects are smaller in magnitude and less robust (columns (4) and (5)). While there could be some small crowding out in the dimensions of policy topics or a shared voter base outside the platform, the attention effects through the platform's follower network dominate.

Finally, we check in column (6) whether viral days have further negative effects on donors' propensity to contribute on top of the negative impact on attention. However, we find that conditional on still going viral, donations do not further decrease. We expect the negative spillover effects on donations to be proportional to the effects on attention.

Perverse Incentives? In Section 3.2 we showed that there is substantial heterogeneity in *who* and *what* goes viral. To have a complete picture of whether Twitter favors MOCs with certain characteristics or distorts incentives to create specific types of messaging and content, we need to understand whether returns are also skewed. Interestingly, as Appendix Figure A6 and A7 show, we do not find evidence of heterogeneity in the size of effects according to different characteristics. This suggests that the main channel through which these content or MOC characteristics impact donations is by changing the probability of going viral. To think through this argument, we consider two specific dimensions of heterogeneity: extreme ideology and negative content.

We begin by considering returns to Twitter for those with extreme ideology, which is important to the extent that is allows us to consider whether Twitter can account for small donors' bias towards political extremists (Bouton et al., 2022). The fact that returns to Twitter virality can be substantial and that the extreme ends of the ideological spectrum overall receive more likes (see Section 3.3) seems to indicate so. In addition, the MOCs who are most prominent on Twitter are polarizing.[14]

[14] For example, by party caucus affiliation, the 3 MOCs who receive the most Twitter likes in our study period are: Alexandria Ocasio-Cortez, Bernard Sanders, Ilhan Omar, Ted Cruz, Jim Jordan, Matt Gaetz.

However, the effects for ideologically extreme candidates are on average small. The probability of going viral for MOCs from the extreme ideological deciles (1, 10) is 80% higher than for MOCs from the central deciles (4-7), meaning they go viral on 46 more days.[15] A viral day increases donations by 4.7% on the intensive margin (Table 3 column (5)), which corresponds to a marginal effect of $128. The difference in the probability of going viral implies an additional $5892 over the full sample period.

We then consider whether there are distorted incentives to focus on negative content when tweeting. In days in which the average sentiment is positive, MOCs have a probability of 7.8% of going viral. Instead, this probability is equal to 22.84% in days in which the average sentiment expressed is negative. As per Figure A7, the intrinsic return to going viral is virtually the same under both conditions. Thus, an MOC that only tweeted negative content would earn approximately $12328 more donations relative to an MOC never doing so. Considering the overall cost of running for office, these higher returns do not appear to be sufficient to distort incentives to focus on negative content.

Finally, we can use the analysis of heterogeneous effects to address to specific concerns regarding the interpretation of our findings. First, it does not appear to be the case that our findings can be explained by MOCs using Twitter to solicit donations. This is apparent from the fact that this type of content is extremely rare, as we mentioned in Section 3.2. Second, it also does not appear to be the case that our findings are driven by external events such as rallies or MOCs' activities in their home district, an omitted variable that might drive both attention on Twitter and donations. Not only are local tweets slightly less likely to go viral, but they also have exactly the same returns in terms of campaign donations.

4.5 Robustness Checks

Robustness to Variables' Definitions. We check the robustness of our results to the use of different measures of Twitter attention and small donations in Appendix Table A4. We find a positive

[15] The probability of going viral is 15.3% for the extreme deciles and 8.5% for the central deciles.

correlation between small donations and tweets' other popularity metrics (retweets, replies, quotes). Interestingly, more intensive interactions such as quotes have higher returns. We also find similar effects for various measures of donations, such all individual donations (i.e., including contributions $\geq$ \$1000), donations through conduits, and donations from donors who contributed less than \$200 to a candidate over the 2019-20 cycle.[16]

Functional Form. In Appendix Table A5, we show further robustness to functional form assumptions. Reassuringly, we find a significant and positive link between Twitter attention and likes across multiple alternative specifications, including linear probability models (LPM) with indicator variables for high-likes and high-donation days (columns (2) and (3)), using logs on a subsample of frequent non-zero donations (column (4)), and the untransformed levels-levels linear relationship (column (5)).

5 Geography-based design

5.1 Framework

Even when controlling for news coverage on traditional media, there are lingering challenges for claiming causality in the relationship we are estimating. Specifically, there is still scope for the donations-likes relationship to be driven by other activities of an MOCs in ways that do not operate via the channel of Twitter. Again, this could be a matter of MOCs' campaign efforts generating donations such that Twitter attention is a secondary by-product of that effort rather than being an actual mechanism that catalyses donations or shocks to the popularity of an MOC outside of social media that are not well captured by cable mentions. In order to establish a Twitter-specific channel we therefore develop a geography-based design that allows cross-sectional variation in Twitter usage to play a role. This is facilitated by the fact that the FEC data contains the location of donors. We therefore build a dyadic panel where we observe the daily donations that an MOC receives from

[16]This definition follows Bouton et al. (2022), who define small donors as individuals who donate less than \$200 to a campaign. Due to the FEC's reporting rules, these donors only appear when donating through a conduit. Contributions by these donors are therefore a subset of donations through conduits.

each of the 48 contiguous US states and the District of Columbia.

Introducing this additional source of variation allows us to include a much richer set of controls. First, we include MOC-by-date fixed effects to absorb all observed and unobserved daily shocks to MOCs' general newsworthiness or other sources of attention, such as the daily, region-unspecific campaign effort. Second, we control for daily regional shocks using state-by-date fixed effects. Third, we include MOC-by-state-by-month fixed effects. MOC-by-state fixed effects pick up the relationship between each MOC and local electorate, such as homophily in unobservable characteristics that confound Twitter use; the further interaction with month allow this to vary over time in the medium run, e.g. to capture that certain politicians could become popular in different parts of the US at different times.

We therefore modify our baseline equation with geographical information and estimate the following specification:

$$y_{ist} = \beta likes_{it} \times users_s + \delta_{ism(t)} + \tau_{it} + \theta_{st} + \varepsilon_{ist}, \tag{3}$$

where y_{its} is the log+1 of the total amount of campaign donations below \$1000 that MOC i receives from state s on date t; $likes_{it}$ is log+1 total twitter likes for MOC i on date 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-date fixed effects; θ_{st} are state-by-date fixed effects. Standard errors are clustered by state and MOC. An estimate of $\beta > 0$ in this specification indicates that donations increase when likes for a given MOC are higher and that this increase tends to emanate from areas with higher rates of Twitter usage.

Equation (3) could still be subject to endogeneity concerns since Twitter usage rates are correlated with a plurality of demographic factors, such as income and education. Therefore, when candidates go viral on Twitter they could simply be more appealing to donors who also use Twitter, e.g. due to policy proposals or other non-Twitter online activity, rather than directly inducing donations through the platform. Most importantly, we might be worried that our estimates might capture the effects of other online social networks or platforms such as Facebook or YouTube, rather than Twitter itself.

We do two things to address these issues. First, we include additional interactions of the MOC-specific $likes_{it}$ time series with cross-sectional state characteristics that are associated with political giving, such as educational attainment, income, urbanization, and Republican vote share. Second, we exploit an instrument created by Müller and Schwarz (2023), which is based on the home towns of the Twitter platform's early adopters at the March 2007 SXSW festival in Austin, Texas.

SXSW 2007 is considered a tipping point for Twitter's popularity and an important early influence on the evolution of its network structure.[17] Twitter's advertising campaign during the 2007 festival resulted in a large increase in the number of daily tweets during the festival and in the year following it. About 60% of early Twitter adopters were connected to SXSW and the platform's growth accelerated disproportionately in counties with SXSW followers who joined Twitter during the 2007 festival (Fujiwara et al. (Forthcoming)). To the extent that early adoption of social media platforms displays persistence, we can use the locations of Twitter's early adopters at SXSW as an instrument for Twitter usage today.

Specifically, we use the log+1 number of SXSW followers in 2007 in state s ($SXSWFollowers_s^{2007}$) interacted with the log+1 number of likes that MOC i receives on date t to instrument $likes_{it} \times users_s$ in equation (3) within a Two-Stage Least Squares (2SLS) framework.[18] The main identifying assumption is that, conditional on our extensive set of fixed effects, the number of SWSX followers in 2007 in a state interacted with the attention that an MOC receives on Twitter must only influence the amount of small donations that a politician receives from the state through the interaction of Twitters users in the state and Twitter attention. In other words, the differences in the locations of SXSW followers who joined Twitter in March 2007 relative to earlier months must not be related to unobserved county characteristics that might in turn explain patterns in campaign contribution.[19]

[17]The SXSW festival is an annual event that showcases various forms of media, including music, film, and interactive technology.

[18]We estimate the first-stage equation $likes_{it} \times users_s = \beta likes_{it} \times SXSWFollowers_s^{2007} + \tau_{it} + \theta_{st} + \varepsilon_{ist}$, where $SXSWFollowers_{s)}^{2007}$ is the log 1+ of the number of Twitter users in each location following the SXSW account after the festival in March 2007 with the other variables being defined as in specification 3.

[19]In their papers, Müller and Schwarz (2023) and Fujiwara et al. (Forthcoming) provide a thorough discussion and extensive evidence of both the relevance of SXSW followers for the growth of local Twitter activity and its exogeneity of this shock to Twitter's geographic diffusion. As we discuss in the results, we follow their steps including similar placebo tests and by further including a set of state-by-date fixed effects.

5.2 Results

Table 4 presents our results from running the OLS and 2SLS models on our dyadic MOC-by-state-by-date panel. Column (1) reports the baseline OLS estimates and shows that MOCs receive significantly more donations from states with higher Twitter use on days when they have higher Twitter popularity. Given that the average log number of Twitter users is equal to 10.7, the marginal effect of a 1% increase in likes for the average state is 0.01 log+1 points, which is very much in line with the estimate from our baseline specification. We do not find a substantial change in our main coefficient when we include additional controls interacted with daily MOC likes (column (2)).

As discussed above, we might still be concerned about similar and unobserveable confounding factors. Hence, we use early Twitter adoption following SXSW 2007 to construct our instrument of Twitter use as described above. In particular, this Twitter-specific shock to local diffusion allows us to also eliminate the effects from other social media platforms.

In column (3) we estimate the reduced form relationship between donations and the interaction of SXSW 2007 followers and likes. This indicates that MOCs receive more donations from states that had more Twitter early adopters when they get more likes. Column (4) follows this up by estimating the 2SLS version, with the first stage presented in column (7). The first stage is strong as per conventional benchmarks and the 2SLS estimates are comparable in magnitude with the OLS. Furthermore, our results remain significant when we adjust our hypothesis tests to be robust to weak instruments (Anderson and Rubin, 1949); we reject the null hypothesis of a zero effect in the second stage at p-value<0.01 (column (4)) and p-value<0.05 (columns (5), (6)). Accounting for the strength our first stage as proposed by Lee et al. (2022), we reject the null at p-value<0.01 (column (4)), p-value<0.05 (column (5)), and p-value<0.1 (column (6))

Table 4: Twitter Likes and Small Donations, Geography-Based Design

	Small donations						Likes X Twitter use		
	OLS			2SLS			2SLS: First stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Likes X Twitter use	0.001***	0.001***		0.001***	0.001**	0.001**			
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)			
Likes X $\text{SXSWFollowers}^{2007}$			0.001***				0.703***	0.696***	0.522***
			(0.000)				(0.061)	(0.120)	(0.107)
Likes X $\text{SXSWFollowers}^{2006}$					0.000	0.000		0.010	0.128
					(0.000)	(0.000)		(0.137)	(0.092)
MOC-by-state-by-month FE	X	X	X	X	X	X	X	X	X
MOC-by-date FE	X	X	X	X	X	X	X	X	X
State-by-date FE	X	X	X	X	X	X	X	X	X
Controls		X				X			X
Obs. (million)	16.4	16.4	16.4	16.4	16.4	16.4	16.4	16.4	16.4
MOCs (clusters)	501	501	501	501	501	501	501	501	501
States (clusters)	49	49	49	49	49	49	49	49	49
F Stat Instrument							130.696	33.805	23.742

This table shows the relationship between Twitter likes and small donations, by Twitter usage at the state level. In our baseline specification, we regress the log+1 of the total amount of donations below $1000 that an MOC receives in a day from a given state on the log+1 of the number of Twitter likes the MOC receives on the same day interacted with the log+1 number of Twitter users in the state, MOC-by-state-by-month fixed effects, MOC-by-date fixed effects, and state-by-date fixed effects (equation (3)). Columns (1) and (2) report OLS estimates, with and without state-level controls interacted with the log+1 number of likes. Column (3) substitutes the log+1 number of Twitter users in the state with the log+1 number of SXSW followers who joined in March 2007 (the reduced form). Columns (4), (5), and (6) report estimates from a 2SLS specification where the interaction between the log+1 of likes and the log+1 of the number of Twitter users in the state is instrumented using the interaction between the log+1 of likes and the log+1 of the number of SXSW followers who joined in March 2007 from the state. Column (5) additionally controls for the interaction of the log+1 of likes and the log+1 number of SXSW followers who joined in 2006 (before the 2007 SXSW festival) from the state, while column (6) additionally includes state-level controls interacted with the log+1 number of likes. Columns (7), (8), and (9) report the first stage for the 2SLS specifications corresponding to columns (4), (5), and (6) respectively. The state-level controls are the share of the population with at least some college, the share of the population living in counties in metropolitan areas, log income per capital, and the Republican vote margin in the 2016 presidential election. Standard errors are clustered at the MOC and state level in all columns.

Importantly, for this empirical strategy to be valid, the differences in locations of SXSW followers who decided to join Twitter in 2007 must be associated with small donations only through the diffusion of Twitter (and not some other unaccounted characteristics of Twitter users). To test this assumption, we follow Müller and Schwarz (2023) and we include pre-shock SXSW followers as an additional control and placebo check. The underlying idea of this check is that the pre-shock diffusion of SXSW followers should capture unobserved characteristics of all SXSW followers and rely on timing of the shock to isolate the effect of the SXSW 2007 festival to Twitter diffusion.

For this, we include pre-2007 SXSW followers interacted with MOCs' likes as an additional control in the 2SLS (column (5)) and add further interactions with socioeconomic controls (column (6)). Importantly, we find that our estimated coefficient does not change and furthermore, that senders of popular tweets do not receive more donations from states with pre-shock early adopters. In line with Fujiwara et al. (Forthcoming)'s result, we find in our first stages that pre-shock followers do not predict later Twitter use when interacted with daily likes (columns (8) and (9)).

Overall, we find that when MOCs go viral on Twitter, they receive significantly more small donations from areas with higher Twitter use. Using a shock to the early diffusion of Twitter as an instrument, we can show that this appears to be a Twitter-specific channel and not driven by other donor and MOC characteristics.

6 Conclusion

Social media is a technological development that has changed the structure of mass media communication. Its innovations of fast endogenous feedback, sensitivity to behavioral biases and massive multi-channel structure have been absorbed into the practice of political campaigning. In particular, the multi-channel structure of social media now allows politicians to communicate almost directly and instantaneously with potential voters and partisan supporters.

The Twitter platform is a pre-eminent vehicle for this type of communication in the US. Our analysis shows that MOC-specific attention on Twitter is strongly associated with donations in a way that is both temporally concentrated around given increases in attention and skewed in its structure. Specifically, the relationship only becomes strongly evident at heightened levels of viral attention. This relationship is further validated by our geography-based analysis that shows that when Twitter attention increases, the flow of donations that follows come from ares with higher levels of Twitter usage.

While our evidence indicates that Twitter is a technology that can be effective for raising donations, this does not occur for everyone: only a very small number of representatives are able to harness attention on the platform to increase donations from small donors. This is reinforced by crowding out effects in attention - when a given MOC goes viral the probability of their peers gaining attention is reduced. Our results therefore point strongly to the operation of a superstar-style market amongst MOCs on the Twitter platform. Although our evidence supports the existence of winner-takes-all effects it is striking how meager the prizes are for the winners. The actual financial benefits to MOCs over the fundraising cycle are modest, reaching around $56,000 for the most popular (top 5) MOCs and $21,000 for the next band of those with substantial visibility (positions 6-50). This corresponds to only 9% (3.3%) of average donations over the cycle that we consider.

Thus, our analysis shows that Twitter is of limited importance when considered along the within-person margin that we have focused on here. But our findings also have some broader implications for the analysis of Twitter's role in electoral politics that are worthy of further study. It is plausible that Twitter plays a role in between-person career success in politics. Growth in average popularity on the platform over time (which our analysis abstracts from) could yield benefits in terms of status and brand building, especially since certain types of content resonate more with its userbase. It may also trigger the attention of big political donors. While the concentration of attention on the platform is comparable to cable television, Twitter might still open the playing field to a different set of players who could not effectively communicate on traditional media but are able to harness this novel communication technology.

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Appendix

Table A1: ANES statistics

	No Twitter	Some Twitter	Daily Twitter	Total
Donation (candidate)	0.138	0.182	0.251	0.160
Donation (party)	0.102	0.094	0.132	0.104
Income $100k+	0.372	0.514	0.511	0.418
College	0.299	0.471	0.470	0.354
City	0.301	0.313	0.354	0.309
Democrat	0.363	0.447	0.581	0.404
Share	0.680	0.208	0.112	0.518

This table shows characteristics of Twitter and non-Twitter usersusing survey data from the 2020 wave of ANES. We report the mean of different variables by respondents' self-reported Twitter use, where No Twitter indicates zero reported Twitter use, Some Twitter indicates occasional Twitter use (between sporadic visits and multiple times per week), and Daily Twitter indicates individuals who use the website at least once per day. Share describes the shares of the different groups of Twitter usage in the data. The variables are coded as follows: Donation (candidate) is an indicator equal to one if the respondent reported contributing money to an individual candidate running for public office during the election year. Donation (party) is an indicator equal to one if the respondent reported contributing money to political party during the election year. Income $> \$100k$ is an indicator equal to one if the respondent reports a family income of $100,000 or higher. College is an indicator equal to one if the respondent reports having a bachelor's degree or higher. City is an indicator equal to one if the respondent reports living in a city. Democrat is an indicator equal to one if the respondent feels connected to the Democratic Party (compared to not feeling connected to a party or feeling connected to the Republican Party).

Table A2: Twitter Likes and Small Donors

	Small Donors			
	Log + 1		Dummy	Log
	(1)	(2)	(3)	(4)
Log likes + 1	0.004***			
	(0.001)			
Top 10% Twitter		0.048***	0.006*	0.043***
		(0.008)	(0.003)	(0.009)
Date-by-party FE	X	X	X	X
MOC-by-month FE	X	X	X	X
Observations	335670	335670	335670	149148
MOCs (clusters)	501	501	501	496
Mean dep. variable	0.874	0.874	0.447	1.653

This table shows the relationship between Twitter likes and the number of small donors. In column (1), we regress the log+1 of the total number of donors who make a contribution below $1000 to an MOC on a given day on the log+1 of the number of Twitter likes the MOC receives on the same day, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). Column (2) estimates the same specification as column (1) but using as the independent variable an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more). While using the same specification and the same independent variable, column (3) defines the outcome as an indicator variable equal to one if an MOC receives a donation from at least one small donor and column (4) as the log of the total number of small donors that donate to an MOC in a day. In column (4), the sample is conditional on receiving at least one donation. Standard errors are clustered at the MOC level.

Table A3: Virality Spillovers

	Top 10% Twitter				Likes	Donations
	(1)	(2)	(3)	(4)	(5)	(6)
Number of viral tweets,	-0.051***			-0.051***	-0.157***	-0.008
weighted	(0.004)			(0.004)	(0.036)	(0.018)
Number of viral tweets,		-0.001**		-0.001**	0.006	0.004
same ideology		(0.001)		(0.001)	(0.006)	(0.005)
Number of viral tweets,			-0.002**	0.001*	-0.002	0.003
same state			(0.001)	(0.001)	(0.010)	(0.007)
Top 10% Twitter						0.083***
						(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

This table shows the crowding out of Twitter attention by estimating the relationship between MOCs' own and others' virality. In column (1), we regress an indicator for the number of likes that an MOC receives on a given day being in the top 10% of the likes distribution (1681 likes or more) on the number of other MOCs also in the top 10% of the likes distribution weighted by the share of Twitter follower overlap that the original MOC has with each politician, date-by-party fixed effects, and MOC-by-month fixed effects . In columns (2) and (3), we use as the independent variable the number of other MOCs in the same DW-nominate decile (column (2)) or from the same state (column (3)) who are also in the top 10% of the likes distribution on the same day. Column (4) reports estimates that includes the three independent variables from columns (1)-(3) in a single specification. Note that due to a technical glitch in the data collection, the folowers' overalp could not be constructed for one MOC (Rep. Scott Moulton), who was therefore omitted from the sample for this analysis. Standard errors are clustered at the MOC level.

Table A4: Twitter Likes and Small Donations, Robustness to Different Measures of Attention and Donations

	Donations					
	Small			All	Conduit	Micro
	(1)	(2)	(3)	(4)	(5)	(6)
Replies	0.017***					
	(0.004)					
Retweets		0.016***				
		(0.003)				
Quotes			0.024***			
			(0.005)			
Log likes + 1				0.013***	0.010***	0.006***
				(0.003)	(0.003)	(0.002)
Date-by-party FE	X	X	X	X	X	X
MOC-by-month FE	X	X	X	X	X	X
Observations	335670	335670	335670	335670	335670	335670
MOCs (clusters)	501	501	501	501	501	501
Mean dep. variable	2.799	2.799	2.799	3.447	2.102	0.867

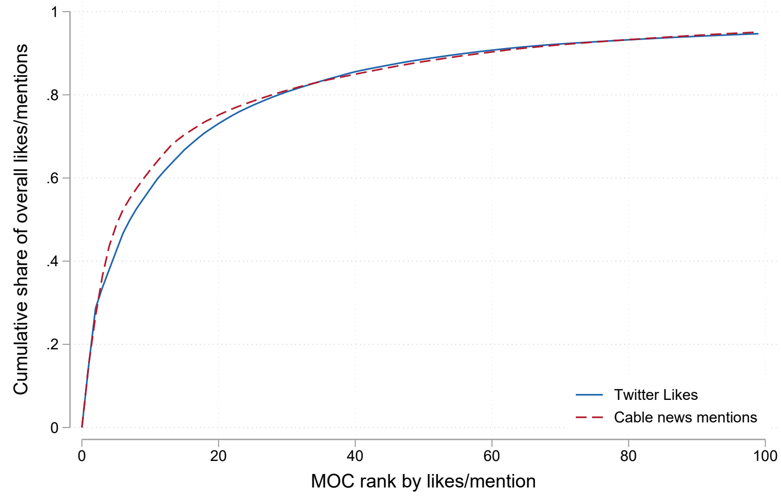
This table shows the robustness of the relationship between Twitter likes and small donations to using different measures of Twitter popularity and different definitions of the outcome variable. In column (1) we regress the log+1 of the total amount of donations below $1000 that an MOC receives on a given day on the log+1 of Twitter replies the MOC receives on the same day, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). In column (2) and (3), we use as the main independent variable the log+1 of retweets and the log+1 of quotes that the MOC receives on the same day respectively. In column (4) we do not restrict donations to be below $1000, while in column (5) we only consider donations received through the conduits Winred and Actblue. Finally, in column (6) the outcome variable is log+1 of the total amount of donations that the MOC receives on a given day from individuals who donote less than $200 to the MOC over the entire election cycle, following Bouton et al. (2022). Standard errors are clustered at the MOC level.

Table A5: Twitter Likes and Small Donations, Robustness to Functional Form Issue

	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		0.016***	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	119744	335670
MOCs (clusters)	501	501	501	486	501
Mean dep. variable	2.799	0.154	0.039	6.322	1219.040

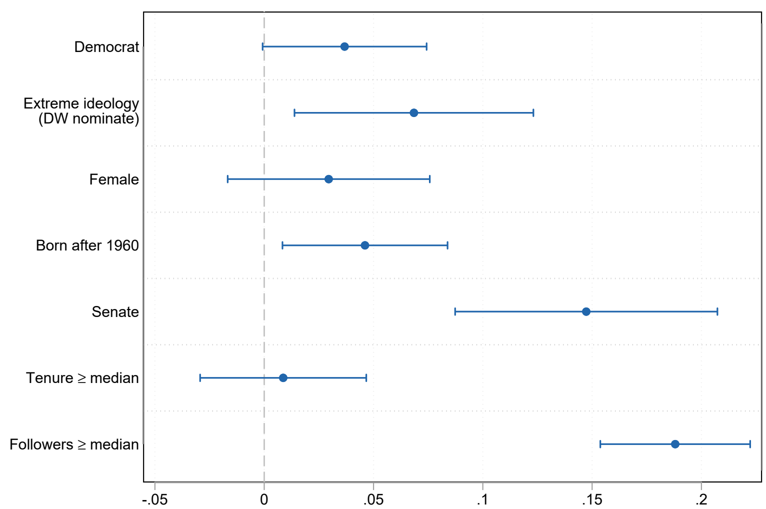
This table shows the robustness of the relationship between Twitter likes and small donations to different functional forms of the main variables. Column (1) replicates our baseline specification (see Table 2 column (4)). In particular, we regress the log+1 of the total amount of donations below \$1000 that an MOC receives on a given day on the log+1 of the total Twitter likes the same MOC receives on the same day, date-by-party fixed effects, and MOC-by-month fixed effects (equation (1)). Columns (2) and (3) use indicator variables for high-contribution and high-popularity observations. The dependent variables are, respectively, an indicator variable equal to 1 if the total amount of donations below \$1000 than an MOC receives in a given day is above \$1000 or above \$5000. The independent variable is an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more). Column (4) uses the log transformation on a subsample where zero donation days are rare: the three months leading up to the 2020 election and MOCs who have less than 5% zero-donation and zero-like days. Column (5) presents results from the linear specification using the untransformed variables. Standard errors are clustered at the MOC level.

Figure A1: Concentration of Twitter Likes and Cable News Mentions



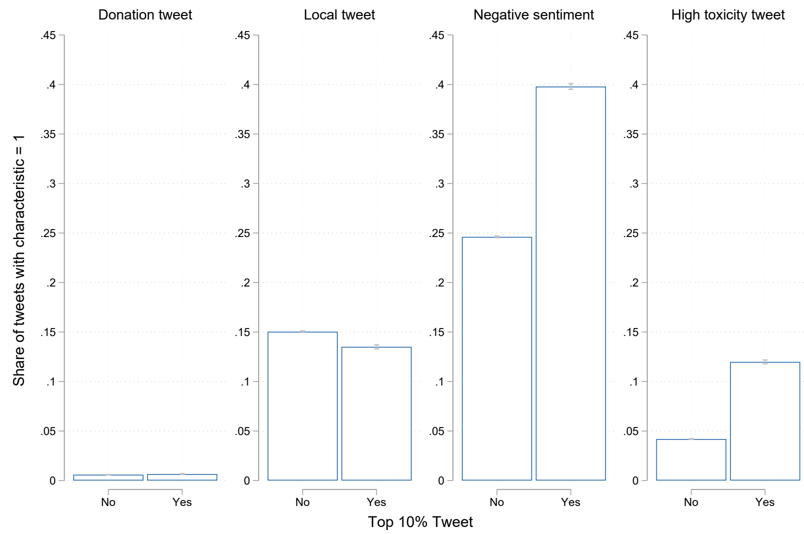
This figure plots the cumulative distribution of politicians' total Twitter likes and cable news mentions by their relative rank, going from the most mentioned (liked) to least. The sample is restricted to the top 100 MOCs by overall Twitter likes and overall cable news mentions respectively.

Figure A2: Likes by MOC Characteristics



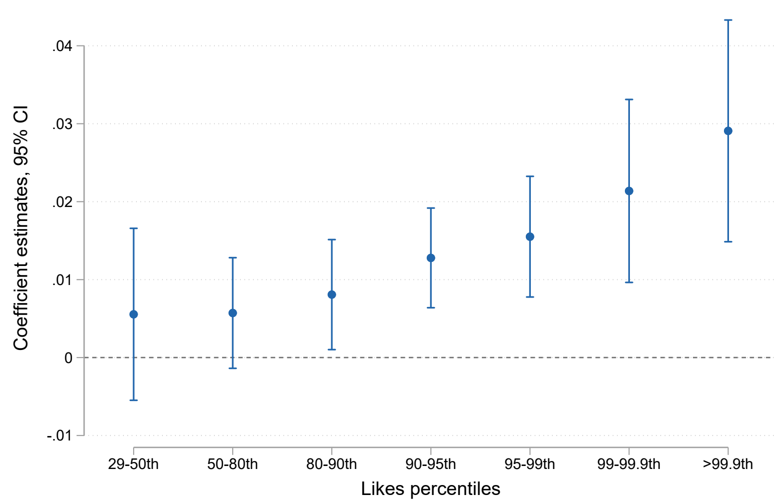
This figure shows the correlation between Twitter likes and MOC characteristics. Using an MOC-by-date panel, we regress an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more) on a specific MOC characteristic and date fixed effects. The effect of each characteristic is estimated from a separate regression. Standard errors are clustered at the MOC level. We define MOCs as having an extreme ideology if their DW nominate score is in the bottom or top decile of the distribution; the definition of all other characteristics should be self-explanatory.

Figure A3: Likes by Tweet Characteristics



This figure shows the share of tweets with a given content by whether the tweet is in the top 10% of the likes distribution or not. A donation tweet is a tweet that links to a donation portal (e.g., WinRed or ActBlue); a local tweet is tweet in which the MOC mentions the name of at least one municipality located in their congressional district; a negative sentiment tweet is a tweet with negative polarity score according to VADER; a high toxicity tweet is a tweet with a toxicity score in the top 5% of the toxicity score distribution according to Google's Perspectives API.

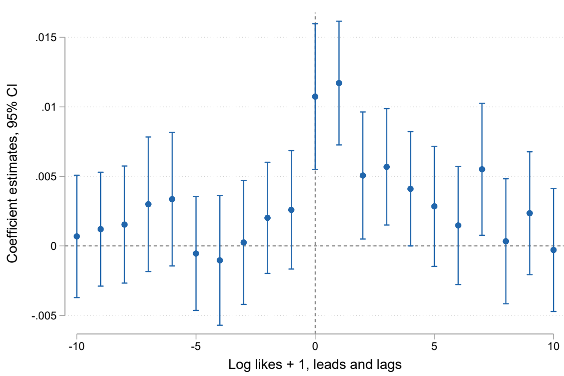
Figure A4: Twitter Likes and Small Donations, Returns by Virality



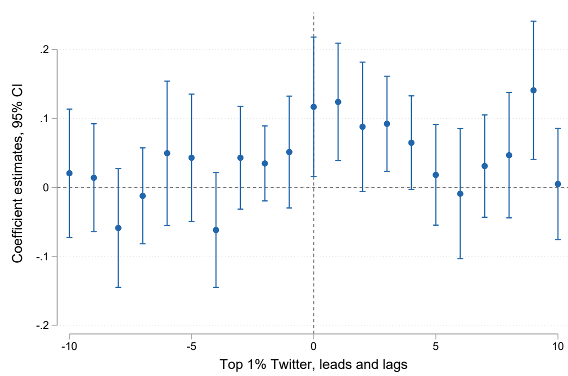
This figure shows how the relationship between Twitter likes and small donations varies depending on the level of virality. In particular, we regress the log+1 of the total amount of donations below $1000 that an MOC receives on a given day on a series of indicators for the number of likes that the MOC receives on the same day being in different percentiles of the likes distribution interacted with the log+1 of the total Twitter likes received, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). The category $29-50th$ includes days with positive likes in the 50th percentile and below, or having between 1 and 31 likes. $50-80th$ indicates days in the 51st to 80th percentile (between 32 and 350 likes). $80-90th$ indicates days in the 81st to 90th percentile (between 351 and 1680 likes). $90-95th$ indicates days in the 91st to 95th percentile (between 1681 and 7,776 likes). $95-99th$ indicates days in the 95th to 99th percentile (between 7,777 and 67,989 likes). $99-99.9th$ indicates days in the 100th percentile, excluding the top .1% of the distribution (between 67,996 and 319,364 likes). $>99.9th$ indicates the top .1% of the distribution (between 319,601 and 3,808,126 likes). Standard errors are clustered at the MOC level.

Figure A5: Twitter Likes and Small Donations, Leads and Lags Robustness

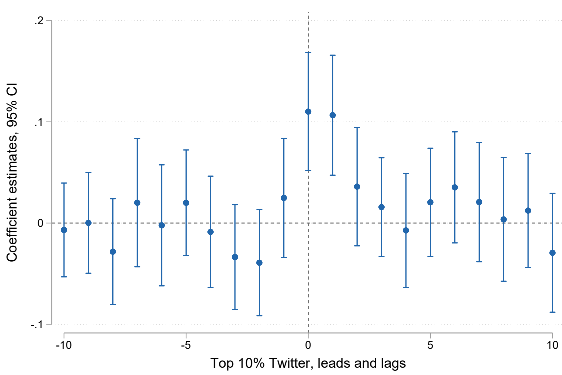
(a) Log 1+Likes



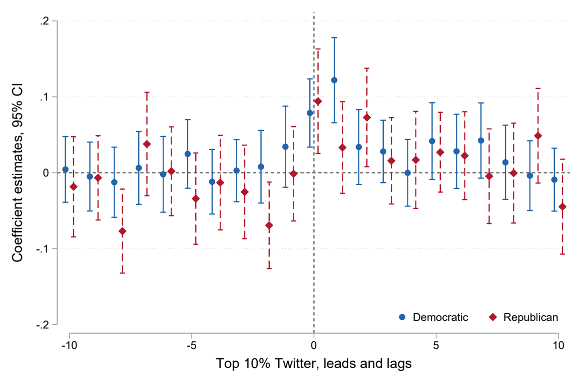
(b) Top 1% Likes



(c) Only 2019

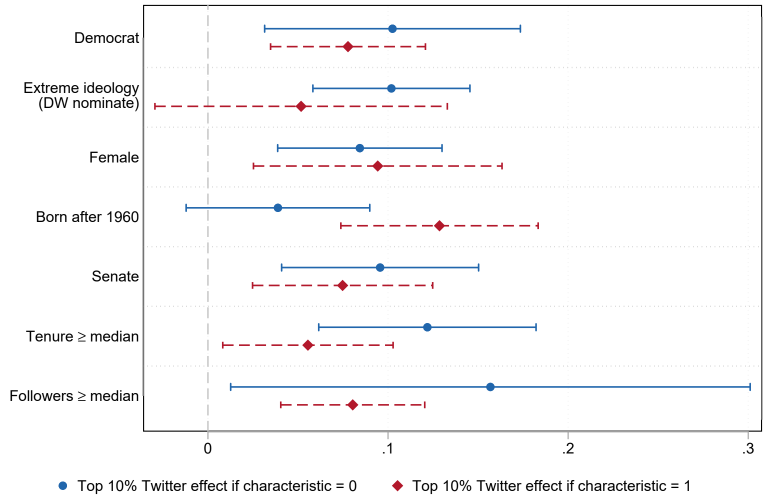


(d) By party



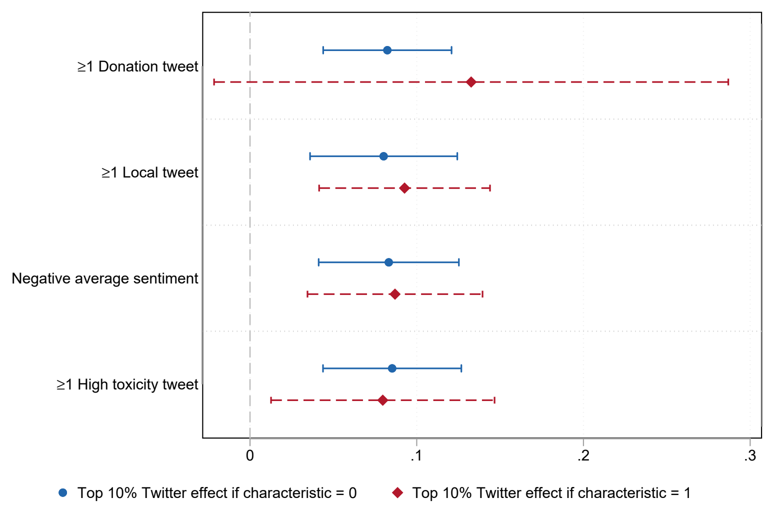
This figure shows the robustness of the dynamic relationship between likes on Twitter and small donations. In panel (a), we regress the log+1 of the total amount of donations below \$1000 that an MOC receives in a day on ten leads and lags of the log+1 of the total Twitter likes the same MOC receives on the same day, date-by-party fixed effects, and MOC-by-month fixed effects. In panel (b), the independent variables are ten leads and lags of an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (67996 likes or more). Panel (c) estimates our main specification (equation (2)) restricting the sample to 2019 (thus, the pre-COVID and pre-election period). Finally, panel (d) estimates our main specification (equation (2)) splitting the sample by whether the MOC is part of the Democratic (blue) or Republican (red) party. Standard errors are clustered at the MOC level.

Figure A6: Effect of Twitter Likes on Small Donations, Heterogeneity by MOC Characteristics



This figure shows heterogeneity of the relationship between Twitter likes and small donations by MOC characteristics. We regress the log+1 of the total amount of donations below \$1000 that an MOC receives on a given day on an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more), the interaction between the same indicator and a specific MOC characteristic, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). We estimate a separate regression for each characteristic and we report in the figure the effect for MOCs who have or do not have the specific characteristic. Standard errors are clustered at the MOC level. We define MOCs as having an extreme ideology if their DW nominate score is in the bottom or top decile of the distribution; the definition of all other characteristics should be self-explanatory.

Figure A7: Effect of Twitter Likes on Small Donations, Heterogeneity by Tweet Content



This figure shows heterogeneity of the relationship between Twitter likes and small donations by tweet content. We regress the log+1 of the total amount of donations below \$1000 that an MOC receives on a given day on an indicator for the number of likes that the MOC receives on the same day being in the top 10% of the likes distribution (1681 likes or more), the interaction between the same indicator and an indicator variable for the characteristic of the tweet content, date-by-party fixed effects, and MOC-by-month fixed effects (similar to equation (1)). We estimate a separate regression for each characteristic and we report in the figure the effect for MOC-days that do or do not display the specific characteristic. Standard errors are clustered at the MOC level. ≥ 1 donation tweet is an indicator variable equal to 1 if the MOC posted the link to a donation portal (e.g., WinRed or ActBlue); ≥ 1 local tweet is an indicator variable equal to 1 if the MOC mentioned the name of a municipality located in their congressional districts at least once; negative average sentiment is an indicator variable equal to 1 if the average sentiment of the tweets is negative (where the sentiment of the tweets is calculated using VADER); ≥ 1 high toxicity tweet is an indicator variable equal to 1 if the MOC had at least one tweet with a toxicity score in the top 5% of the toxicity score distribution according to Google's Perspectives API.