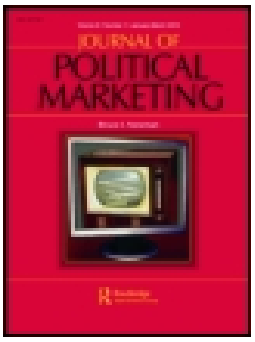

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Twitter Influencers in the 2016 US Congressional Races

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In this paper, I outline a method for collecting Twitter data to identify two types of political actors that are increasingly prominent in social media environments: influential politicians and politicized influencers. Influential politicians are those whose messages are readily retweeted *(i.e., shared) while politicized influencers are users who retweet politicians' messages and who themselves receive many retweets. I find that highly retweeted politicized influencers tend not to have formal political affiliations, and so are politically influential but not in an official political capacity. I then relate the Twitter data to electoral outcomes of the 2016 US congressional races. I find that, for richer candidates and incumbents, receiving many retweets is associated with higher vote percentages while, for poorer candidates and challengers, receiving retweets from highly retweeted users is associated with higher vote percentages. Better-off candidates should thus strive to be influential politicians, whereas worse-off candidates should aim to get retweeted by influential users. I argue that the rise of social media begs for a study of what we might call* influencer politics, *which allows for new empirical investigations into the role that social media play in shaping the democratic process.*

KEYWORDS campaign strategy, celebrity politics, everyday makers, influencer politics, social media

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INTRODUCTION

"Retweets do not equal endorsements." This phrase has become commonplace among users on the social news platform Twitter to highlight that *retweeting*, or sharing, another user's message does not imply support for the message's content. While some Twitter users may indeed retweet a message simply to inform or amuse, or with tongue in cheek, the difference between retweets and endorsements is not always clear-cut. For example, Nikki Haley, the US Ambassador to the United Nations and former Governor and Congresswoman, recently violated the Hatch Act when she retweeted a tweet by President Donald Trump that endorsed then-congressional candidate Ralph Norman (Link 2017). The Hatch Act states that federal employees cannot use their office to engage in political activity, and Haley was accused of effectively endorsing Norman herself when she retweeted Trump's endorsement.

While there is still debate about when retweets should be treated as endorsements, this incident points to the fact that retweets can and often are used to endorse political candidates. Moreover, even when a retweet does not constitute an explicit endorsement of a candidate's message, it is a meaningful act in that it increases exposure to the message's content. As a result, several scholars have found that retweets capture a Twitter user's *influence* in getting messages to spread (Kwak et al. 2010; Cha et al. 2010). Ackland (2013) argues that retweets are likely the best measure of a Twitter user's influence because they reflect a "clear indication that someone has made a conscious decision to pass information on" (Ackland 2013, p. 110). Regardless of whether or not retweets serve to endorse a political candidate's messages, they represent users' willingness to engage with these messages and thus with the candidate's campaign more broadly.

In this paper, I show that retweets can be useful for understanding the role that social media play in shaping democratic outcomes, for two distinct reasons. The first has to do with *who gets retweeted*, which can shed light on which politicians are able to harness attention and gain influence on Twitter. The second reason has to do with *who does the retweeting*, which can illuminate which Twitter users share politicians' messages and the extent that they themselves are influential. Retweets are thus useful for identifying both influential politicians and politicized influencers (i.e. popular users who engage with politicians' messages). This distinction echoes that made in the literature on celebrity politics between "celebrity politicians" and "politicized celebrities" (e.g. Wheeler 2013), albeit with a broader and more digitally oriented notion of influence than celebrityhood. The rise of social media begs for such a broadening, to what we might call *influencer politics*; shifting focus to social media users that are influential for politics but who may not be celebrities in the traditional sense.

To show how studying retweets can aid in our understanding of how social media shape democratic outcomes, I outline a method for collecting Twitter data that captures both how readily politicians get retweeted and the popularity of those who retweet them. I categorize the most influential retweeters and find that most of them do not have an official political affiliation. These influencers are thus good candidates for what Bang (2003) calls *everyday makers* – people without an official role in politics but who are politically relevant nonetheless. I then relate data from Twitter to electoral outcomes of 2016 US Congressional races. I find that the number of retweets a candidate receives is positively associated with vote percentages if they are better-funded than their competitor or are incumbents while retweets from influential users increase vote percentages of poorer candidates and challengers. These findings suggest that well-off candidates should strive to be influential politicians while worse-off candidates should aim to get their messages shared by politicized influencers.

The remainder of the paper is organized as follows. In the next section, I build on prior work on celebrity politics to argue that retweets, when viewed as social network links connecting politicians and everyday makers, can help to broaden the scope of celebrity politics to include social media influencers who may not be celebrities. I then outline a method for collecting data that capture the Twitter success of candidates who ran in the 2016 US congressional races, and summarize the data and models that I use to relate retweets to electoral outcomes. I present the results of estimating several specifications of my model in the penultimate section, and conclude with a discussion of the findings and directions for future work.

INFLUENTIAL POLITICIANS AND POLITICIZED INFLUENCERS

In his recent book on celebrity politics, Wheeler (2013) contrasts two types of actors who have brought celebrityhood into the political sphere. The first is the celebrity politician—a traditional politician who has "incorporated matters of performance, personalization, branding and public relations into the heart of their political representation" (Wheeler 2013, p. 87). The second is the politicized celebrity—a celebrity who has gained recognition outside of politics, but leverages this popularity to raise "public awareness concerning [political] campaigns" and provide "credibility for issue-driven campaigns within policy agendas" (Wheeler 2013, p. 114).

The distinction between celebrity politicians and politicized celebrities is attributed to Street (2004), who makes the case that we can no longer view celebrityhood as a phenomenon that occurs tangentially to politics. In contrast to previous work, which often treats celebrity politics with "mockery and hand-wringing," Street (2004) argues that "political ventures into the world of popular culture are a legitimate part of the complex ways in which political representation functions in modern democracies" (Street 2004, p. 436). Some have criticized Street's typology as overly simple, preferring a more nuanced approach that delineates between different types of celebrities (e.g. Marsh et al. 2010). However, Street (2012) argues that his simple distinction "allows us to ask how the uses of show business and popular culture affect political practice, where more multifaceted definitions tend to accommodate celebrities within the complexities of existing political processes" (Street 2012, p. 347).

In addition to providing a more focused lens into how celebrity politics differs from other forms of political practice, Street's (2004) typology is also advantageous because it more easily accommodates a network-based view of celebrity politics. Recently, several scholars (e.g. Marsh et al. 2010; Wheeler 2012) have urged that the study of celebrity politics could benefit from a more explicit acknowledgment of Bang's (2003) ideas about networked governance and the decline of formal hierarchies. In this light, the recent prominence of celebrity politicians and politicized celebrities can both be seen as responses to more general socio-structural trends that have given rise to a *network society* (Castells 2000; Rainie and Wellman 2014). As Bang and Esmark (2009) point out, these trends are intrinsically tied to the emergence of new information and communication technologies that continue to shape modern politics in profound ways.

While Bang's (2003) ideas about networked governance have been applied to the study of celebrity politics, they do not speak exclusively about the role of celebrities. The very same technologies that are leading us into a network society, according to Bang and Esmark (2009)—weblogs, social network sites, and other virtual worlds—bestow new political identities and capital to a larger set of actors than we might deem to be celebrities. Bang (2003) refers to this new generation of politically influential (though not necessarily politically affiliated) citizens as everyday makers—those who "live their lives on the borderline between a political system and its environment, fluctuating back and forth, sometimes taking part in the system's strategic activities, sometimes escaping and circumventing them to pursue their own small tactics" (Bang 2003, p. 21).

Reflecting on Bang's (2003) recognition of the increasingly important role of everyday makers, I argue that the rise of social media begs for a broader notion of celebrity politics that we might call *influencer politics*. Moving away from celebrities to focus on social media influencers provides several benefits. First, this allows us to incorporate everyday makers that are influential for politics but may not be celebrities in the traditional sense. Second, empirical studies that have searched for effects of celebrity involvement in political processes find that celebrities only have limited impacts (e.g. Thrall et al. 2008). Broadening the scope of celebrityhood to include social media influencers can thus help to expand the search and identify new avenues where the effects of popularity may be taking hold. Finally, the study of social media influencers easily lends itself to empirical study since measures of social media influence are well established (e.g. Kwak et al. 2010; Cha et al. 2010).

To demonstrate how a shift away from celebrities can accommodate an empirical and network-based view of political influence, I adapt Street's (2004) typology and employ an established measure of influence on Twitter: retweets. In simple terms, a retweet is a decision by a Twitter user to share another user's message. In Figure 1, arrows link two social network *nodes* – one representing the politician whose message is shared and the other the person who shares it. The size of a node captures its *influence*, or the number of retweets they have received on their own messages. In this model, influential politicians are assumed to have more retweets than non-influential politicians while politicized influencers have more retweets than politicized non-influencers. Figure 1 thus captures influential politicians and politicized influencers in the larger nodes labeled "politician" and "retweeter," respectively. Next, I discuss how Twitter data can be collected to identify influential politicians and politicized influencers.

TWITTER DATA COLLECTION

Many studies of Twitter use in political contexts focus on collecting and analyzing messages that contain particular keywords (or hashtags) – for example, those that point to political parties that are involved in an election (Dang-Xuan et al. 2013) or to candidates participating in a televised

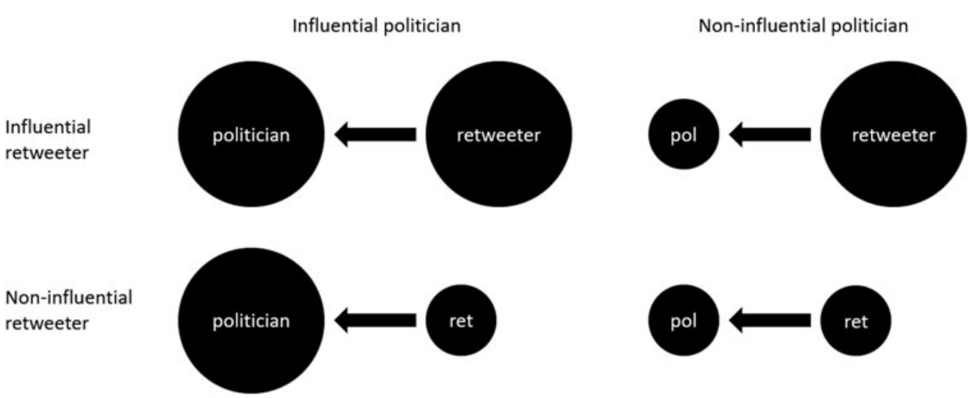

FIGURE 1 Distinguishing between influential and non-influential politicians and retweeters.

debate (Freelon and Karpf 2015). While this method has been used to generate important insights about the role that social media play in politics, it also has some notable drawbacks. In particular, many relevant tweets may not contain the keywords that are chosen for sampling so that relying on a set of keywords may result in missing key aspects of the conversation surrounding the event of interest. Relatedly, González-Bailón et al. (2012) show that Twitter's Search API, the most common tool used by researchers to extract tweets containing specific keywords, over-samples the activity of central users while leaving out much of the peripheral activity.

In this study, I use a snowball sampling method similar, in spirit, to Wu et al.'s (2011).[1] Instead of constraining data collection to textual features of tweets, I start with a list of Twitter accounts used by candidates who ran in the 2016 US House and Senate elections.[2] For each candidate, I collect the original tweets generated by their account in the 3 months prior to the election – from August 3rd to the morning of November 8, 2016. For each tweet, I then collect the users who retweeted (i.e. shared) it. Finally, I repeat the procedure for users who retweeted at least one candidate account, collecting their tweets over the same time period and the users who retweeted these tweets. This approach let me construct a *retweet network* for each candidate, capturing both users who retweeted the candidate and the extent that they retweeted each other. Figure 2 depicts my data collection approach.

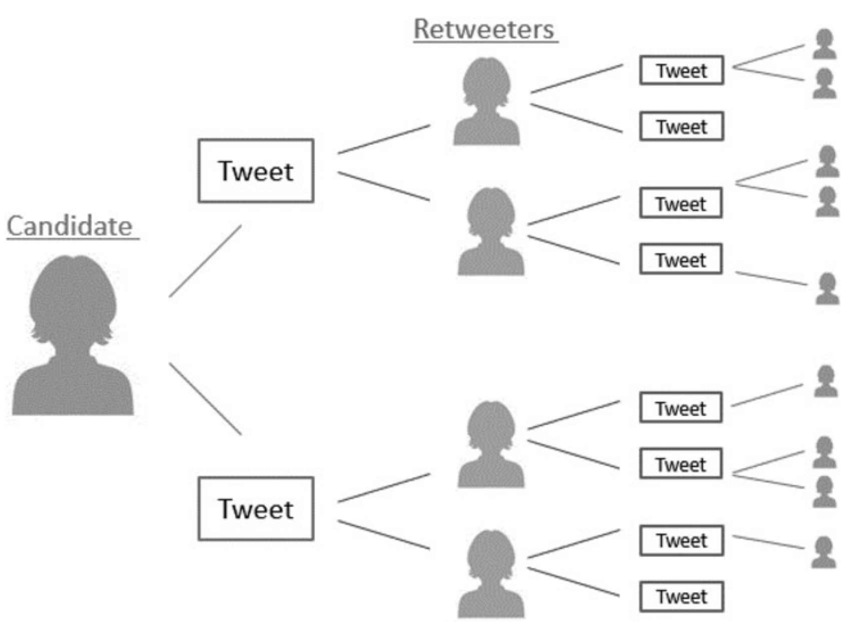

FIGURE 2 Using snowball sampling to capture a candidate's retweet network.

Focusing on users who retweet a candidate's messages has several advantages. First, as previously discussed, retweets are a natural measure of a candidate's influence because they reflect an explicit decision on behalf of users to share the candidate's messages (Ackland 2013). Second, this approach allows for the identification of users who engage with political candidates' messages, but whom the researcher may not be aware of prior to data collection. Finally, by starting with a candidate's Twitter account, the approach allows for the calculation of candidate-specific metrics that can then be related to politically relevant variables, like electoral outcomes and campaign finance activity. It is this combination of Twitter and other politically relevant variables that I turn to next.

DATA SUMMARY AND ANALYSIS

In addition to collecting data about candidates' tweets and retweeters, I also consult the Federal Election Commission's (FEC) website for data about the state in which candidates were running, the seat for which they were competing (i.e. House or Senate), as well as each candidate's party affiliation, incumbency status, and campaign disbursements (i.e. expenses). In each race, I only include the two candidates with the highest percentage of votes, and only candidates who faced opposition in the general election. The FEC labels candidates who defeat an incumbent in their party's primary as challengers, so I recode such cases as open races (since there is no incumbent running in the general election). To control for each candidate's exposure on traditional media, I follow DiGrazia et al. (2013) and count mentions of each candidate's full name in CNN transcripts between August 3rd and November 8th, 2016 – the same time period used for

TABLE 1 Summary Statistics of Candidate Variables

	Mean	Std. Dev.	Minimum	Maximum
Senate	0.11	0.31	0	1
Incumbent	0.54	0.50	0	1
Challenger	0.35	0.48	0	1
Republican	0.47	0.50	0	1
Third-Party	0.01	0.12	0	1
CNN Mentions	33.38	307.22	0	5356
Disbursements	2.14	3.54	0	25.28
Tweets	60.55	31.26	1	194
Retweets	28.86	277.31	0	5430
Likes	49.48	463.87	0	9067
Retweets of RTers	2.42	3.27	0	24.61
Likes of RTers	4.07	5.29	0	42.47

Note: Number of candidates = 406.

Twitter data collection. My final dataset includes all of these variables for 406 candidates competing in 263 congressional races.[3]

In Table 1, I present summary statistics of the candidate-specific variables. *Senate* is an indicator equal to 1 for candidates running in Senate races and 0 for those running in House races. *Incumbent* and *Challenger* indicate a candidate's incumbency and challenger status, and are both set equal to 0 for candidates in open races. *Republican* and *Third-Party* indicate the party affiliation of the candidate, and are both set to 0 for Democrat candidates. *CNN Mentions* captures the number of times a candidate's name appeared in CNN transcripts during the 3 months prior to the election. *Disbursements* captures a candidate's total campaign expenses in 2016 and was gathered using the TTL_DISB column of the FEC Candidate Financial Summary and divided by one million to ease interpretation (Margolin et al. 2016).[4] *Tweets* captures how many messages were posted by the candidate's account, while *Retweets* and *Likes* capture the average number of times that these tweets were retweeted and liked, respectively.[5] Finally, *Retweets of RTers* and *Likes of RTers* capture the average number of retweets and likes that candidates' retweeters received on their tweets, respectively.

By combining the Twitter data with candidates' party affiliations, I can visualize the social network of congressional candidates and their

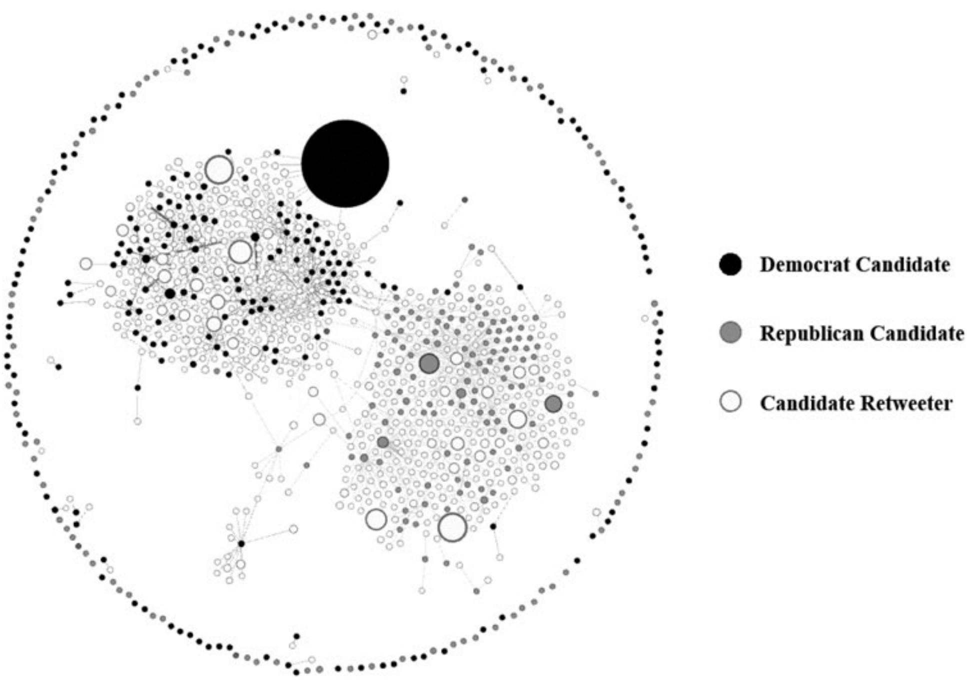

FIGURE 3 The social network of candidates and retweeters.

retweeters (Figure 3). The nodes in this network include all of the candidates in the dataset, but only retweeters who received an average of 10 retweets on their tweets.[6] Black and gray nodes represent Democrat and Republican candidates, respectively, whereas white nodes represent retweeters. A node's size reflects how many retweets they received on their tweets, on average. Larger black and gray nodes thus represent influential politicians while larger white nodes represent politicized influencers. Edges in the network exist when a retweeter either retweeted a candidate or another retweeter, and the thickness of an edge represents the number of times (i.e. tweets) that the retweeter retweeted.

A few features of this network are worth discussing in more detail. First, similar to the findings of Conover et al. (2011), there appears to be a clear partizan divide between Democrat and Republican nodes. Democrat nodes are largely of similar size, with the exception of Rep. John Lewis, whose tweets, on average, received 5430 retweets in the months leading up to the election. In comparison, no other node in the network, candidate or retweeter, received more than an average of one thousand retweets per tweet. The two largest Republican nodes are Rep. Trey Gowdy (closer to the center; average retweets = 994) and Rep. Jason Chaffetz (further from the center; average retweets = 792). Next, I discuss categorization of the most influential retweeter accounts – the largest white nodes in the social network visualization.[7]

Categorizing Politicized Influencers

The Twitter data collection approach outlined above allows for the identification of politicized influencers – influential Twitter users who engage with politicians' messages. With the help of two research assistants, I categorize the most influential of these users – those with at least 50 retweets on their messages, on average – to understand more about them. In particular, the main goal of the categorization was to assess whether these influencers tend to have formal political affiliations (i.e. are politicians or are employed by a political group), or instead might fall under Bang's (2003) designation of everyday maker (i.e. politically influential but not in an official role). In total, 109 retweeter accounts received an average of more than 50 retweets per tweet. This sample of retweeter accounts was used for categorization.

The research assistants were instructed to assign each retweeter account any applicable labels from the following list: Politician, Political Group, Political Advocate (i.e. employed by a political group), Activist, Journalist, Artist, Business Person, News Organization, Non-Political Group, Other. During the coding process, the assistants identified two categories that were added to the list: Academic and Athlete. Any account for which the two assistants did not agree on any label was reviewed and assigned a label by the author (six accounts). When the assistants assigned multiple labels to an account, the most appropriate label was chosen by the author (16 accounts). This coding process thus resulted in a single label for each retweeter account.

Figure 4 depicts the distribution of labels assigned to these influential retweeter accounts. The most popular label was Activist (25 accounts). Highly retweeted Activist accounts tended to retweet Republican candidate accounts and include @Braveheart_USA (average retweets = 946), @ChatRevolve (average retweets = 627), and @TomFitton (average retweets = 303). The most popular labels after Activist were Politician and Political Group (20 accounts each), followed by Journalist (11 accounts) and Political Advocate (10 accounts). Highly retweeted non-Activist accounts include @nick2crosby (Political Advocate; average retweets = 925), @MaddowBlog (Journalist; average retweets = 727), and @NubianAwakening (Journalist; average retweets = 513). A full list of these 109 influential retweeter accounts and their assigned labels is available from the author upon request.

To assess whether politicized influencers tend to have formal political roles, I divide up the category labels based on whether or not they imply

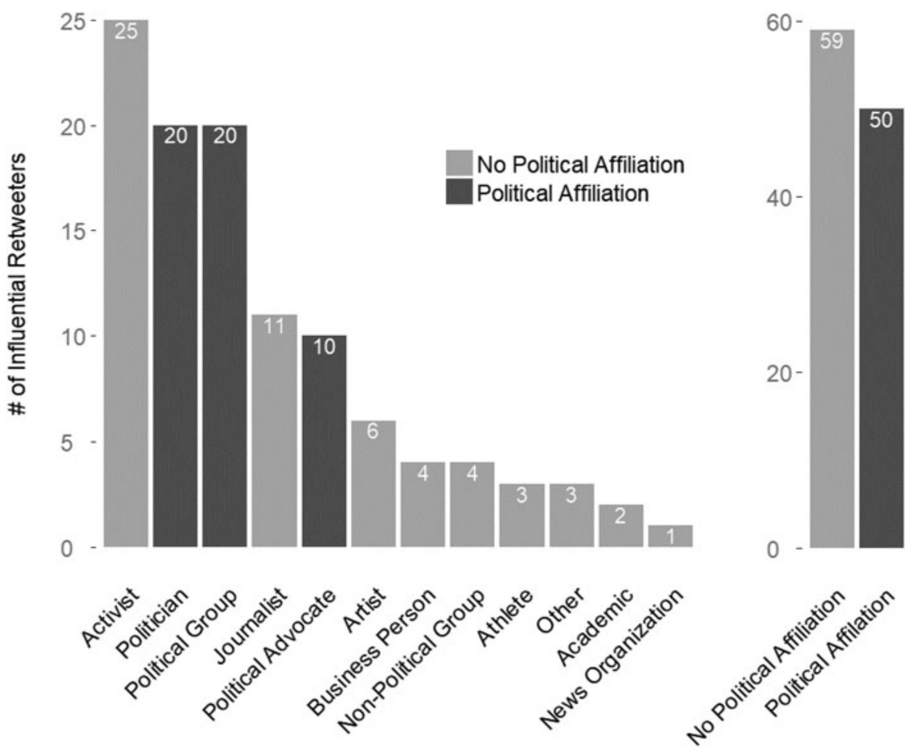

FIGURE 4 Number of politicized influencers by type and political affiliation.

an official political affiliation. Labels that do not imply an official political affiliation include Activist, Journalist, Artist, Business Person, Non-Political Group, Athlete, Other, Academic, and News Organization (59 accounts). Labels that do indicate an official political affiliation include Politician, Political Group, and Political Advocate (50 accounts). Most accounts were found not to have an official political affiliation, supporting Bang's (2003) suggestion that many people who are influential for modern politics – in this case, those broadening exposure to political candidates' messages – do not have formal political roles and might fall under the designation of everyday maker. Next, I investigate the role of politicized influencers and influential politicians in shaping electoral outcomes.

Relating Retweets to Electoral Outcomes

Before describing my empirical analysis, I provide model-free evidence for the effects of interest. The outcome variable in all of the models presented is a candidate's percentage of votes in the 2016 general election.[8] To contrast how Twitter metrics relate to vote percentages of better and worse-off candidates, I divide up the candidates in two ways. First, I consider the top- and low-funded candidates to be those with more and fewer disbursements in a given race, respectively. Second, I only consider incumbents and challengers while excluding candidates in open races (i.e. races with

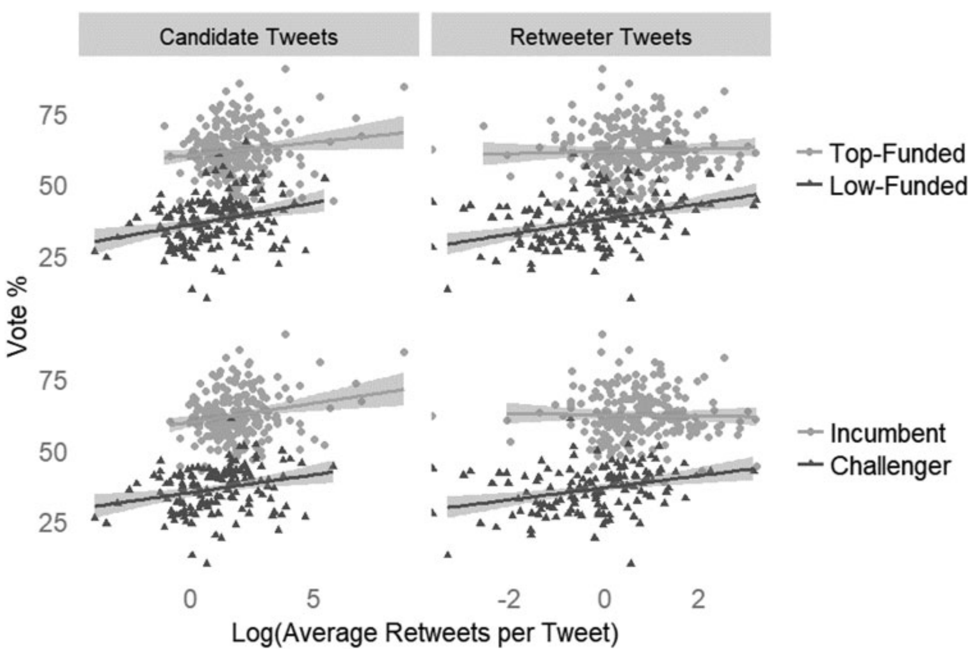

FIGURE 5 Electoral outcomes by candidate and retweeter retweets.

no incumbent running in the general election). Figure 5 depicts the relationship between votes and retweets of candidates (left panel) and their retweeters (right panel).[9] The left panel shows a positive relationship between the number of retweets a candidate receives and their vote percentage. Moreover, the relationship does not appear to vary much by financial position or incumbency. The right panel, which depicts the relationship between vote percentages and the number of retweets candidates' retweeters received, tells a different story. While being retweeted by highly retweeted users is related to higher vote percentages for low-funded candidates and challengers, the relationship for top-funded candidates and incumbents is flat. Retweets from influential users thus only appear to help disadvantaged candidates.

To test for the statistical significance of these relationships, I model vote percentages as a function of the Twitter metrics and control variables. I estimate the following specification separately for top- and low-funded candidates, and for incumbents and challengers:

$$\text{Vote }\% = \alpha + \mathrm{B} \times \text{Twitter Metrics} + \Gamma \times \text{Control Variables}$$

Next, I simultaneously include better- and worse-off candidates in the same regression (i.e. top- and low-funded candidates in one specification, and incumbents and challengers in another). I include the indicator Dis, which is set to 1 for the disadvantaged candidate, and interact it with the set of Twitter metrics and control variables:

$$\begin{gathered}\text{Vote }\% = \alpha_1 + \mathrm{B}_1 \times \text{Twitter Metrics} + \Gamma_1 \times \text{Control Variables} \\ \alpha_2 \times \text{Dis} + \mathrm{B}_2 \times \text{Twitter Metrics} \times \text{Dis} + \Gamma_2 \times \text{Control Variables} \times \text{Dis}\end{gathered}$$

I take into account multicollinearity between the candidate variables when considering which to simultaneously include in the same regression. In Table 2, I present a correlation matrix of the candidate variables. This

TABLE 2 Correlation Matrix of Candidate Variables

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Z_1	Z_2	Z_3	Z_4
Senate (X_1)											
Incumbent (X_2)	–0.05										
Challenger (X_3)	0.06	–0.80									
Republican (X_4)	0.02	0.31	–0.32								
Third-Party (X_5)	0.02	–0.05	0.04	–0.12							
CNN Mentions (X_6)	0.11	0.09	–0.07	0.10	–0.01						
Disbursements (X_7)	0.65	0.14	–0.15	0.08	–0.03	0.31					
Tweets (Z_1)	0.25	0.15	–0.10	0.09	0.04	0.00	0.24				
Retweets (Z_2)	0.00	0.07	–0.05	–0.03	–0.01	0.09	0.03	–0.05			
Likes (Z_3)	0.01	0.07	–0.05	–0.02	–0.01	0.10	0.03	–0.05	0.99		
Retweets of RTers (Z_4)	–0.13	0.26	–0.23	0.12	–0.01	–0.04	–0.03	0.03	–0.04	–0.04	
Likes of RTers (Z_5)	–0.10	0.27	–0.24	0.11	–0.01	–0.04	0.00	0.05	–0.03	–0.03	0.97

Note: Number of candidates = 406.

table reveals two correlations that are problematically close to one: between the retweets and likes that candidates' tweets received ($\rho = 0.99$), and between the retweets and likes that candidates' retweeters' tweets received (ρ=.97). This relationship is hardly surprising – when a tweet is retweeted, it receives more exposure and can thus be liked by more users. Moreover, both measures likely indicate the inherent quality of a tweet. For this reason, in my analyses, I only include the number of retweets that a candidate or her retweeters received. All of the findings are nearly identical when including likes instead of retweets. I do not present these additional analyses here, but they are available upon request. Next, I discuss the results of estimating several specifications of the models described in this section.

EMPIRICAL RESULTS

I estimate the two specifications described in the previous section using ordinary least squares (OLS) regression. In Table 3, I present the results when splitting candidates based on their financial position relative to their competitor in the race. The two leftmost models include estimates for top- and low-funded candidates separately while the rightmost model includes both candidates in a single regression. These estimates indicate that different Twitter metrics may influence the vote percentages of top- and low-

TABLE 3 OLS Regression Models of Vote % by Top- and Low-Funded Candidates

	Separate Models				Single Model with Interaction			
	Top-Funded		Low-Funded		Baseline		× Low-Funded	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Constant	61.0**	1.78	40.2**	2.13	61.0**	1.75	−20.8**	2.80
Twitter Metrics								
Tweets	.004	.015	.020	.021	.004	.015	.016	.026
Retweets	.004**	.001	−.006	.038	.004**	.001	−.010	.039
Retweets of RTers	−.017	.151	.426**	.190	−.017	.145	.443*	.246
Control Variables								
Senate	3.79	2.47	−3.66	2.26	−3.79	2.43	−7.44**	3.36
Incumbent	5.56**	1.66	−1.05	3.21	5.56**	1.63	−6.60*	3.68
Challenger	−8.22**	3.02	−6.47**	1.76	−8.21**	2.98	1.74	3.48
Republican	−4.43**	1.01	.049	1.29	−4.43**	.993	4.48**	1.66
Third-Party	−8.27	7.49	−5.09	3.34	−8.27	7.37	−3.18	8.14
CNN Mentions	.002	.001	−.005	.007	.002	.001	−.007	.007
Disbursements	-.730**	.205	1.26**	.349	-.730**	.201	1.99**	.411
Adjusted R^2	.258		.284		.750			
Observations	244		162		406			

*$p < 0.1$; **$p < 0.05$.

funded candidates. While the vote percentages of top-funded candidates significantly increase with the number of retweets they receive, the vote percentages of low-funded candidates increase with the number of retweets their retweeters receive. This is consistent with the notion that richer candidates should strive to be influential on Twitter, whereas poorer candidates should aim to receive retweets from influential Twitter users.

Estimates of the control variables also reveal differences between the predictors of vote percentages for top- and low-funded candidates. For richer candidates, incumbency increases vote percentages while being a Republican decreases vote percentages (compared to being a Democrat). Richer and poorer candidates both have lower vote percentages when facing an incumbent in the race. Finally, consistent with previous work (e.g. Jacobson 1990), money only increases vote percentages for financially disadvantaged candidates.

In Table 4, I present the results when splitting candidates based on incumbency. The two leftmost models include estimates for incumbents and challengers separately while the rightmost model includes both in a single regression. I exclude open races in these analyses, so the number of observations is lower than when comparing top- and low-funded candidates. The results of this alternative specification are even stronger than to those presented in Table 3. Incumbents benefit from having their tweets widely retweeted while challengers benefit much more from having their tweets retweeted by influential users. The estimates of the control variables are mostly similar to those presented in Table 3. One notable difference is

TABLE 4 OLS Regression Models of Vote % by Incumbents and Challengers

	Separate Models				Single Model with Interaction			
	Incumbent		Challenger		Baseline		× Challenger	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	67.5**	1.29	42.2**	3.20	67.5**	1.28	−26.4**	3.86
Twitter Metrics								
Tweets	−.006	.015	.020	.020	−.006	.015	.026	.028
Retweets	.004**	.001	−.049*	.027	.004**	.001	−.053*	.027
Retweets of RTers	−.032	.131	.545**	.252	−.032	.130	.577**	.288
Control Variables								
Senate	5.56**	2.43	−2.75	2.20	5.56**	2.39	−8.30**	3.29
Low-Funded	−10.9**	2.33	−7.52**	2.96	−10.9**	2.30	3.39	3.80
Republican	−5.16**	1.00	−1.86	1.35	−5.16**	.986	3.29*	1.70
Third-Party	−6.21	5.09	−6.13	4.00	−6.21	5.02	.085	6.48
CNN Mentions	.002	.001	.016	.020	.002*	.001	.014	.020
Disbursements	-.755**	.215	.665**	.285	-.755**	.212	1.42**	.360
Adjusted R^2	.295		.229		.787			
Observations	221		141		362			

$^*p < 0.1$; $^{**}p < 0.05$.

that vote percentages of incumbents is higher in Senate races that House races, while the opposite is true for challengers.

DISCUSSION, LIMITATIONS, AND FUTURE WORK

In this paper, I outline a method for collecting Twitter data to identify two types of political actors that are increasingly prominent in social media environments: influential politicians and politicized influencers. My method relies on previous studies of Twitter to argue that a good measure of a user's influence on Twitter is the extent that their tweets are shared, or *retweeted* (Kwak et al. 2010, Cha et al. 2010). Influential politicians are those that receive many retweets while politicized influencers are Twitter users who engage with politicians' messages and who themselves receive many retweets. I find that a majority of the most highly retweeted politicized influencers do not have formal political affiliations, and so are good candidates for what Bang (2003) calls *everyday maker*s – people who are politically influential, but not in an official role. Building on the literature on celebrity politics, I suggest that the rise of social media begs for a broadening of celebrityhood to include social media influencers that are important for politics, but who may not be celebrities in the traditional sense. I argue that a shift away from celebrity to what we might call *influencer politics* allows for new empirical investigations into the role that social media play in shaping democratic outcomes.

To show how identifying influencers can help us understand the role that social media play in shaping the democratic process, I relate retweets to electoral outcomes of the 2016 US congressional races. I find that, for richer candidates and incumbents, receiving many retweets is associated with higher vote percentages, whereas for poorer candidates and challengers receiving retweets from highly retweeted users is associated with higher vote percentages. Better-off candidates should thus strive to be influential politicians, whereas worse-off candidates should aim to get engagement from politicized influencers. These findings shed light on the complicated relationship between social media and democratic outcomes. On one hand, better-off political candidates who gain influence on Twitter are likely to overwhelm their worse-off competitors. However, by leveraging their influencer status in the political arena, politicized influencers offer a chance for disadvantaged candidates to harness the energy and popularity of social media influencers indirectly. Influential politicians and politicized influencers thus have opposing effects on the competitiveness of elections.

There are a couple of limitations to this study that warrant further discussion. First, while the empirical models that I use provide evidence for a significant relationship between retweets and votes, these results cannot be interpreted as strictly causal in nature. The control variables that I include in the models help to control for other determinants of vote percentages, but there are likely omitted variables that also predict electoral outcomes. If these variables were correlated with the variables of interest, namely the number of retweets that candidates and their retweeters received, such endogeneity would bias the estimates presented. However, the Twitter data collection method that I outline in this paper provides an important starting point in the empirical study of influencer politics. Future studies could strengthen causal identification using retweets of political messages as natural experiments, contrasting political opinions before and after these messages are shared.

A second limitation of this study is that I only relate direct retweets of a candidate's messages to electoral outcomes. This study thus excludes what is known on Twitter as *quote tweets* – retweets that also include commentary on behalf of the retweeter. Thus, while this study focused on direct sharing of candidates' messages, important insights could likely be gleaned by studying how politicians' messages are commented on. For example, if politicized influencers comment negatively on a politicians' message, this could have interesting but yet unknown effects on democratic outcomes. Given that mere mentions of a candidate's name on Twitter are positively associated with vote percentages (DiGrazia et al. 2013), studying how social media influencers discuss candidates on Twitter could be another fruitful direction for future research on influencer politics

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NOTES

1. An important distinction is that Wu et al. (2011) sift through Twitter Lists that include a focal set of users while my method focuses on users who retweet the focal set.
2. About 10% of the candidates used multiple Twitter accounts. In these cases, tweets from all identified accounts were collected and collapsed for the candidate.

3. One of the research assistants who helped with the Twitter data collection did not properly complete the task so that data were not obtained for congressional races in Illinois, Maryland, Oklahoma, New Mexico, or West Virginia.

4. Data on candidate disbursements were obtained from https://classic.fec.gov/finance/disclosure/ftpsum.shtml

5. On Twitter, a retweet is an explicit decision to share a tweet, while a like indicates favorability of the tweet but without an explicit decision to share it.

6. A social network including all retweeters features more than 30 thousand nodes and 100 thousand edges, which was too large to visualize in a meaningful way.

7. An interactive social network visualization, which allows visitors to zoom in and out of the social network and to select specific nodes to reveal candidate information and Twitter IDs of their retweeters, is available at http://www.yotamshmargad.com/congress2016.

8. Obtained from https://transition.fec.gov/pubrec/electionresults.shtml. For races in Louisiana, I use vote percentages in the runoff elections. For races in Connecticut, New York, and South Carolina, I use combined vote percentages.

9. I use the log transformation of the retweet variables here to better depict differences between candidates. The empirical analyses in this paper use the non-transformed variables, but the results are qualitatively similar when using the transformed variables. Estimates using log transformations of these variables are available upon request.

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AUTHOR NOTE

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