



## Do Likes of Trump's Tweets Predict His Popularity?

As Benjamin Franklin famously said, “in this world nothing can be said to be certain, except death, taxes, and tweets by President Trump.” Even after more than 14 months in office, we react like a flock of startled chickens each time another presidential tweet lands with a thud in our midst. The best and brightest among us try to parse meaning from these 140-280 character missives until the next tweet sends us off clucking in surprise once again.

Looking for meaning in any given tweet might be a fool's errand, but his tweets taken together might provide some information. 538's Nate Silver, for example, [found](#) that more “Twitter rage” was weakly correlated with lower popularity ratings, though the finding was not statistically significant.

Silver may have been looking in the wrong place for meaning in his tweets, though. Rather than thinking about how his tweets affect people's opinions, it is possible that the causality runs differently, and that Trump's popularity can be predicted by how people engage with his tweets. In particular, do more “likes” correspond to higher approval ratings?

In short, the answer is yes. Every thousand likes correlates to about 0.02 percent decrease in his disapproval ratings and 0.015 percent increase in his approval ratings. These are meaningful magnitudes given that each tweet accrues about 87,000 likes, on average. To the extent this relationship continues in the future, Twitter may provide a tool for knowing Trump's approval in something closer to real time than traditional polls provide.

### Data

The [Trump Twitter Archive](#) records information about Trump's tweets, including the date and time, device type sending the tweet, number of retweets, number of likes, whether the tweet is itself a retweet, and the content of the tweet itself. Data on Trump's popularity comes from UCSB's “[American Presidency Project](#),” which archives Gallup poll results.

Combining the data requires matching tweets to the time period covered in the polling data. For example, the data report an approval rating of 38 percent for the period January 8-14, 2018. However, the president tweeted 45 times, not including retweets, during that time. Thus, an observation in the final dataset is the time period dictated by the polling data. I normalize the tweet data by dividing likes and retweets by the number of tweets in that time period.

The table below shows summary statistics for the dataset.

	Mean	Min	Max
Likes per tweet	87,384	50,285	227,824
RTs per tweet	19,998	11,276	48536

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Table 1: Summary Statistics Note: Excludes tweets that Trump retweeted.

Figure 1 shows the average number of likes and retweets. Figure 2 shows Trump’s approval and disapproval ratings as measured by Gallup.

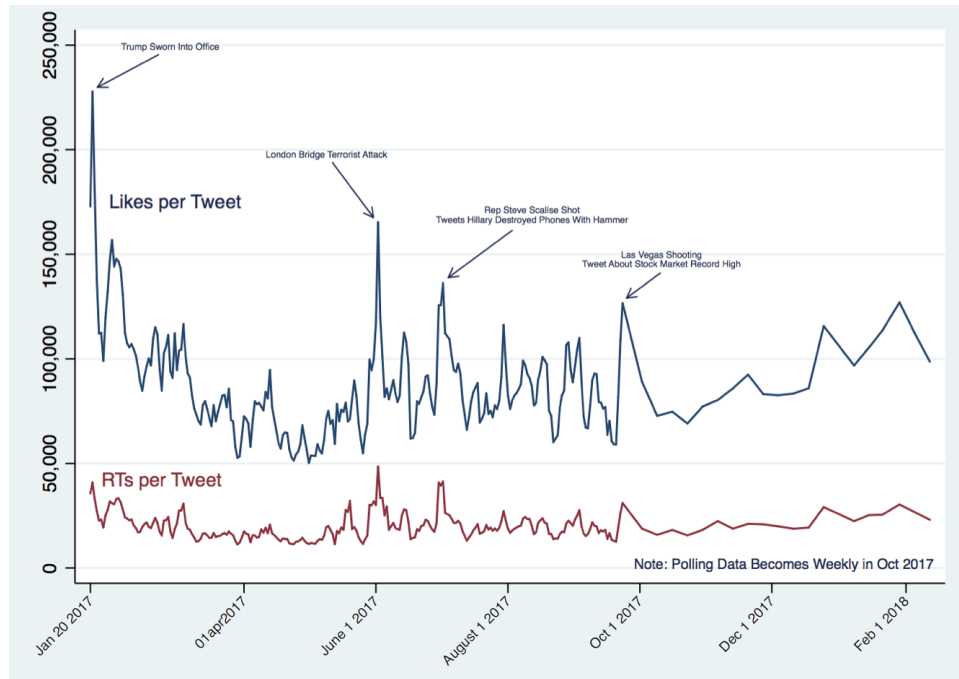


Figure 1: Likes and Retweets per Tweet from Jan 20, 2017 – Feb 18, 2018

### Do Likes Predict Approval?

Here I test the hypothesis that likes are correlated with approval ratings. It seems a sensible hypothesis: if more people like the president, more people should “like” his tweets.

Figure 3 graphs Trump’s approval ratings and the average number of likes per tweet during the relevant time period. They do appear correlated, though the match is not perfect.

The next step is to explore the relationship econometrically. I regress Trump’s approval ratings, and then his disapproval ratings, on the average number of likes per tweet. The regression also includes a time trend to account for underlying trends unrelated to tweets, month fixed effects to control for exogenous events affecting his popularity, the number of tweets in the time period, and the number of days in the time period.

Table 2 summarizes the results of these regressions (full results in the appendix). The analysis shows a positive relationship between likes and approval, a negative relationship between likes and disapproval, and a negative relationship between likes and percent whose opinion is “unsure.” All are statistically significant, although the relationship between likes and approval is somewhat less robust than the others—statistical significance at conventional levels is sensitive to the specification.

In short, the results show that more likes is associated with higher approval, lower disapproval, and lower “unsure” ratings.

Figure 4 shows the predicted values based on the regression output.

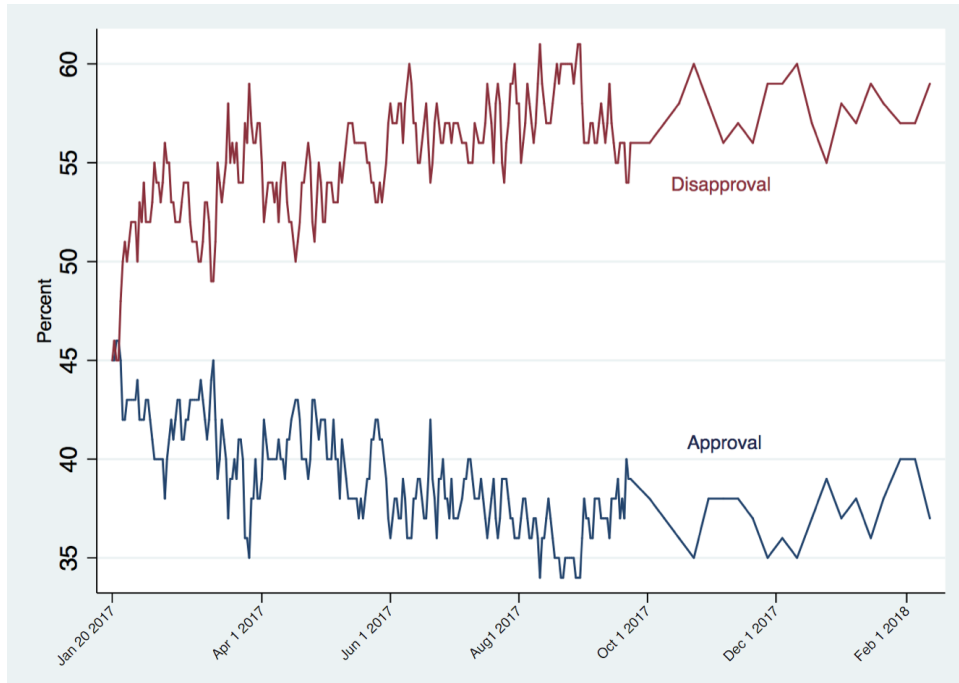


Figure 2: Trump Approval and Disapproval Ratings

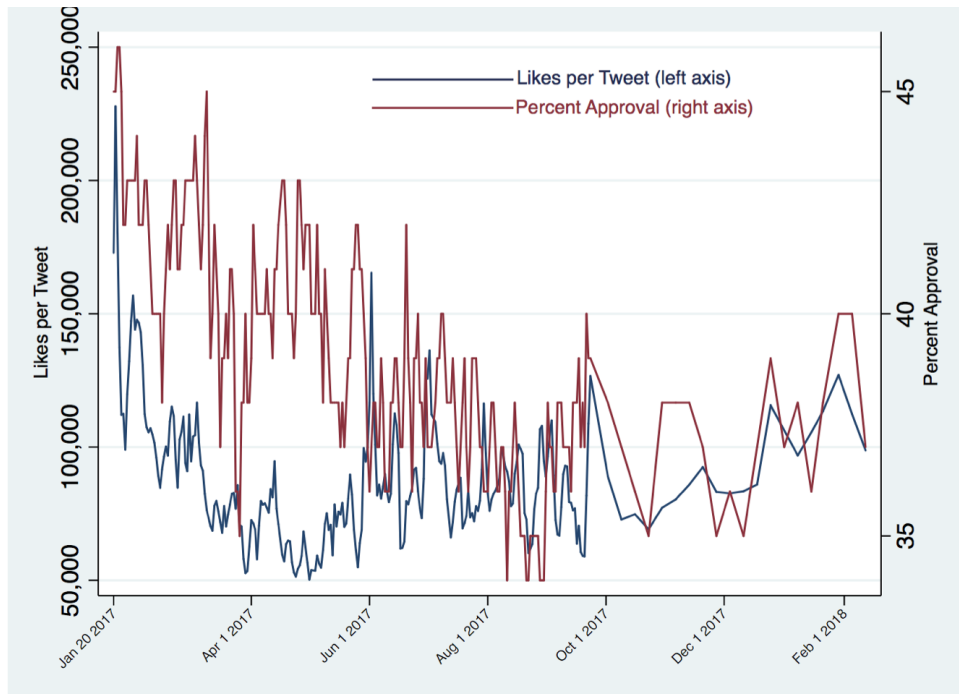


Figure 3: Tweet Likes and Approval

	percent approve	Percent disapprove	Percent unsure
Likes per 1000 Tweets	0.01* (2.44)	-0.02** (-2.92)	-0.03** (-2.78)
Time Trend	-0.02*** (-3.54)	0.04*** (5.46)	0.07*** (4.70)
Number Days in Period	0.18 (0.46)	-0.61 (-1.38)	-0.80 (-0.98)
Number Tweets per Period	0.04** (2.65)	-0.03* (-2.14)	-0.07* (-2.46)
Constant	40.74*** (34.60)	53.41*** (41.08)	12.67*** (5.29)
Month fixed effects?	Yes	Yes	Yes
Observations	262	262	262
$R^2$	0.68	0.69	0.70

$t$  statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Figure 4: Likes and Polling Outcomes

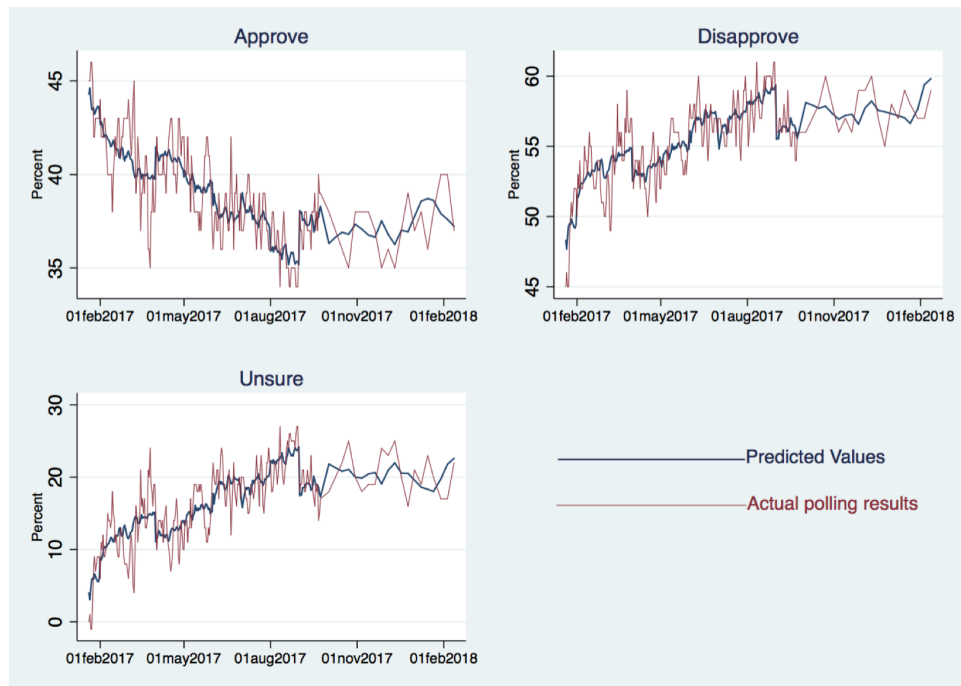


Figure 5: Popularity Ratings Predicted by Regression Model

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## Implications and Conclusion

Polls are typically conducted over several days, so they report only some average over the days the poll was conducted. Tweets and likes happen in real time. As a result, likes provide a mechanism for determining changes in Trump's popularity in the present, rather than learning how people felt several days prior.

Of course, this analysis has problems. First, it takes time for likes to accumulate. Presumably they asymptote to their final level for any given tweet over some period of time. To accurately predict popularity based on likes we need to know how quickly the number of likes approaches its final level. Presumably this information is knowable. Second, a large number of other, exogenous, events may affect his popularity in ways that are difficult to know in real time. Finally, the relationship identified here may not persist.

Nevertheless, likes of Trump's tweets appear to be correlated with his popularity, meaning Twitter provides a tool for evaluating approval ratings in real time.

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**Appendix** *t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 2: Likes and Approval Ratings

	percent approval	percent approval	percent approval	percent approval
Likes per 1000 Tweets	0.01* (2.56)	0.01 (1.87)	0.01 (1.71)	0.01* (2.44)
Time Trend	-0.02*** (-16.86)	-0.02*** (-6.85)	-0.02*** (-3.48)	-0.02*** (-3.54)
Number Days in Period			0.34 (0.84)	0.18 (0.46)
Number Tweets per Period				0.04** (2.65)
Constant	41.18*** (84.82)	42.26*** (45.97)	41.71*** (36.82)	40.74*** (34.60)
Month fixed effects?	No	Yes	Yes	Yes
Observations	262	262	262	262
$R^2$	0.55	0.67	0.67	0.68

Table 3: Likes and Disapproval Ratings

	percent disapproval	percent disapproval	percent disapproval	percent disapproval
Likes per Tweets (1000s)	-0.02** (-3.30)	-0.02** (-2.66)	-0.01* (-2.37)	-0.02** (-2.92)
Time Trend	0.03*** (15.69)	0.03*** (9.68)	0.04*** (5.40)	0.04*** (5.46)
Number Days in Period			-0.75 (-1.69)	-0.61 (-1.38)
Number Tweets per Period				-0.03* (-2.14)
Constant	53.44*** (95.70)	51.32*** (50.58)	52.55*** (42.22)	53.41*** (41.08)
Month fixed effects? No	Yes	Yes	Yes	
Observations	262	262	262	262
$R^2$	0.53	0.68	0.68	0.69

Table 4: Likes and "Unsure"

	dk	dk	dk	dk
Likes per 1000 Tweets	-0.03** (-3.05)	-0.03* (-2.36)	-0.02* (-2.13)	-0.03** (-2.78)
Time Trend	0.05*** (16.76)	0.05*** (8.62)	0.07*** (4.63)	0.07*** (4.70)
Number Days in Period			-1.09 (-1.33)	-0.80 (-0.98)
Number Tweets per Period				-0.07* (-2.46)
Constant	12.26*** (12.12)	9.06*** (4.84)	10.84*** (4.71)	12.67*** (5.29)
Month fixed effects? No	Yes	Yes	Yes	
Observations	262	262	262	262
$R^2$	0.56	0.69	0.69	0.70