1 Introduction

Several studies have shown that sexism played a role in the 2016 U.S. presidential election in which Donald Trump defeated Hilary Clinton. (Valentino, 2018; Bracic et al., 2019; Schaffner et al., 2018; Bock et al., 2017; Stewart et al., 2019). In this paper, we further the understanding of the impact of sexism on the outcome of the 2016 presidential election by presenting evidence on the role that Trump's actions played in inflaming the sexism that enhanced his vote share. Specifically, we analyze Tweets by Trump that insulted Clinton (or women generally) and find that increases in insulting Trump Tweets are associated with an increase in sexist Google searches and that the areas in which sexism had the greatest sensitivity to Trump Tweets had lower support for Clinton relative to their previous support for Obama.

Corbi and Pichetti (2020) and Owen and Wei (2020) are the two most closely related papers to this work. Both use Google search data to identify the sexism of a geographic area and relate that sexism to Trump's vote share in the 2016 election. Both find that Trump garnered a higher share of the votes in areas that performed more sexist searches. While Corbi and Pichetti use searches for one sexist word to identify sexism, Owen and Wei (2020) use a sexism index developed in Owen and Wei (2021) that captures several dimensions of hostile sexism. In this paper, we use Owen and Wei's broader sexism index because the Tweets issued by Trump exhibited multiple dimensions of sexism, including depicting women as objects, as rude and evil, or as dumb and emotional.

Our work contributes to our understanding of how sexism influenced the election by directly relating statements made by one of the candidates to greater expressions of sexism online. The fact that these online expressions of sexism are systematically related to voting outcomes and that relative support for Trump was higher in areas where sexism responded more to his Tweets suggest a channel through which sexism was activated in a politically consequential way.

2 Data and Methods

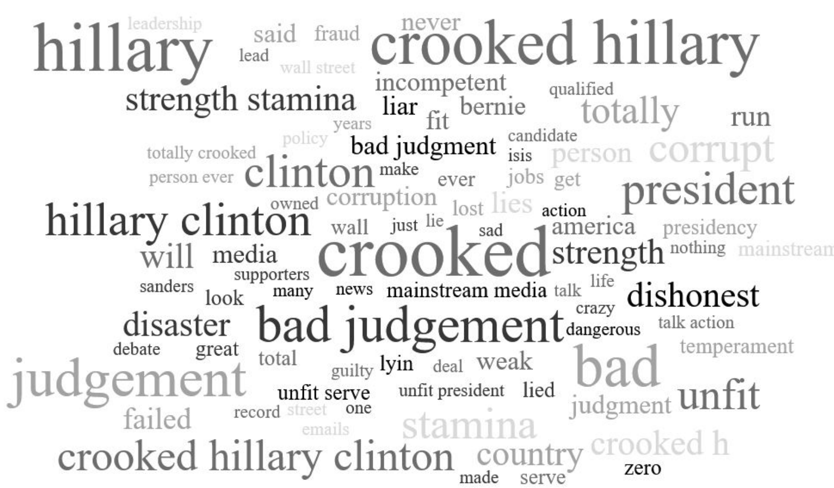
We obtain Trump Tweets that insult Clinton and other women from a list compiled by Lee and Quealy (2016) from the public Twitter search API. Their list is at the weekly frequency and includes insulting Trump Tweets, the specific person, place, or thing insulted by the Tweet, and the specific phrase used for the insult. We count in each month the number of Tweets that insult Clinton and the number of Tweets that insult women other than Clinton.

Figure 1A depicts the content of Trump Tweets that insulted Clinton and indicates that the most common adjectives used to describe her are "crooked", "corrupt", and "dishonest". Figure 1B depicts the content of Tweets that insulted women other than Clinton, showing the most common adjectives to be words like "crazy", "nervous", and "goofy."[1] The language in these Tweets is consistent with themes that women are rude and evil or dumb and emotional, which are both components of hostile sexism.

[1] The figures are generated from performing N-gram analysis on the phrases used to insult Clinton and women other than Clinton.

Figure 2 shows the number of Trump Tweets each month that insult either Clinton or all women (excluding Clinton) over time. As to be expected, Tweets insulting Clinton increased dramatically in the run up to the 2016 election, reaching a maximum of 132 in July 2016. Trump continued to Tweet about Clinton after the election, but much less frequently and Tweets insulting other women became relatively more common.

Figure 1A. Content of Tweets Insulting Clinton

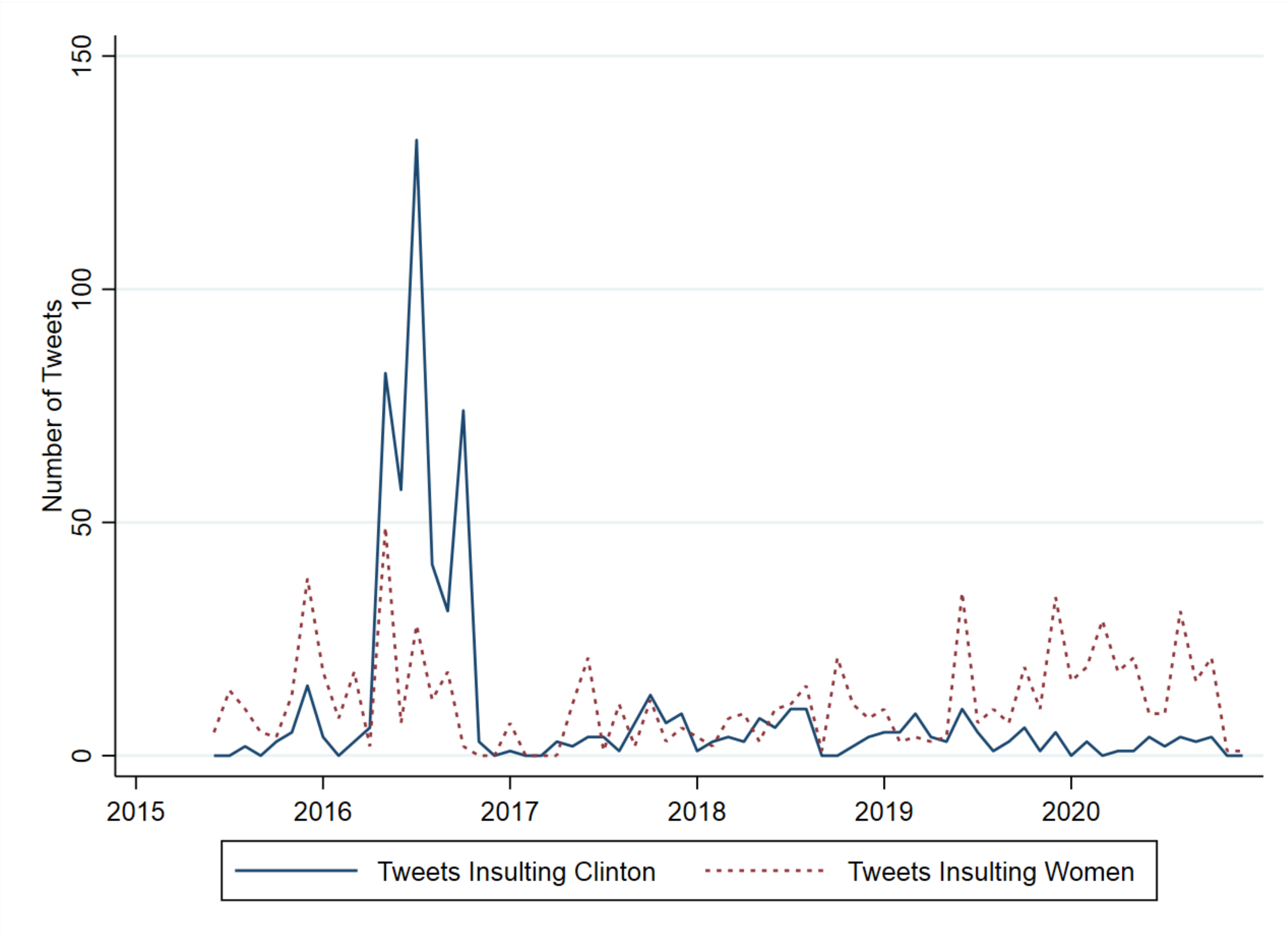


Notes: Figure 1A shows the most frequent N-grams for Tweets insulting Clinton, with larger font sizes indicating higher frequencies.

Figure 1B. Content of Tweets Insulting Women Other than Clinton

Notes: Figure 1B shows the most frequent N-grams for Tweets that insult women other than Clinton, with larger font sizes indicating higher frequencies.

Figure 2. Trump Twitter Insults Over Time.



We use these Tweets in both a monthly time series and a panel analysis. In the time series estimations, we estimate the following equation:

$$\text{Sexism}_t = \beta_0 + \beta_1 \text{Twitter}_t + \text{X}_t + \varepsilon_t, \quad (1)$$

where *Sexism*$_t$ is a Google-based sexism index from Owen and Wei (2021) and *Twitter*$_t$ is the count of Trump Tweets that insult Clinton or women other than Clinton in month *t*. X_t, a vector, accounts for long-term trends and seasonality by including year dummies and their interactions with quadratic time trends. In the panel analysis, we are able to exploit time-series variation in sexist Google searches for each of 208 different media markets. Specifically, in the base specification, we estimate:

$$\text{Sexism}_{it} = \beta_0 + \beta_1 \text{Twitter}_t + \text{X}_t + \delta_i + \varepsilon_{it}, \quad (2)$$

where *Sexism*$_{it}$ is the Google-based sexism index at the media market level, $Twitter_t$ and X_t are the same variables defined in (1), and δ_i is a set of media market fixed effects. The media market is an appropriate level to study local culture because media markets are defined as a collection of counties that receive the same television broadcasting and all residents within a media market will be exposed to similar local media.

The dependent variables in equations 1 and 2 are an area's sexism measure, normalized so that it has a mean of 0 and a standard deviation of 1.[2] Its construction is described in detail in Owen and Wei (2021), but essentially, it captures the search volume of sixteen sexist words, with greater values indicating higher search volumes. The words together capture hostile sexism, and each word represents one of the three themes of hostile sexism: women as objects, women as rude and evil, or women as dumb and emotional. As such, it is a more comprehensive measure of sexism than that used by Corbi and Pichetti (2020) who use one of the sixteen words in the index.

The panel data allows us to also estimate how residents in different areas differed in their response to Trump's Tweets and correlate those differential responses to election outcomes. We estimate our final specification in two steps, where in the first step, we use a similar setup as equation 2 but estimate separate coefficients for each media market *i*:

$$\text{Sexism}_{i,t} = \delta_i + \beta_i \text{Twitter}_t + \text{X}_t + \varepsilon_{it}. \quad (3)$$

With β_i, we capture how the sexism of media market *i* responded to Trump Tweets. We also include in some specifications Tweets insulting men and estimate a separate coefficient for it in each media market. In a second step, we correlate the β_is with election outcomes by estimating a regression with Clinton's 2016 vote share relative to either Obama's 2012 or Obama 2008 vote share as the dependent variable. We control for an area's sexism index in the second step to address the concern that people who did not vote for Clinton may have been more predisposed to conducting sexist Google searches in general, regardless of Trump's Twitter activity.

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[2] The normalization implies search volumes above the mean have a positive value for the index and search volumes below the mean have a negative value. The sexism indices at the time-series, panel, and cross-sectional levels are normalized separately with the mean and standard deviation of each.

Table 1 summarizes the data used in our estimations. Our Twitter data is monthly and begins when Trump formally announced his candidacy in June 2015 and ends in December 2020. As indicated by positive average coefficients from Equation 3, Tweets insulting either Clinton or women generally in the average media market are associated with an increase in sexism and Tweets insulting men are associated with a decrease.

Table 1. Summary Statistics.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Sexism Index (Time-Series)	195	0	1.000	-2.070	1.909
Sexism Index (Panel)	42,250	0	1.000	-3.332	4.861
Sexism Index (Cross-Section)	209	0	1.000	-4.702	4.324
Tweets Insulting Clinton	67	9.537	21.65	0	132
Tweets Insulting Women	67	10.85	10.21	0	44
Tweets Insulting Men	68	55.09	37.46	6	184
%Clinton2016 - %Obama2012	206	-0.0271	0.0621	-0.168	0.155
%Clinton2016 - %Obama2008	206	-0.0493	0.0708	-0.200	0.137
%Obama2012 - %Obama2008	208	-0.0212	0.0325	-0.107	0.268
Clinton Coefficient	208	0	1.000	-2.437	2.879
Female Coefficient	208	0	1.000	-2.410	2.947
Male Coeff. (From Clinton Regression)	208	0	1.000	-3.497	2.850
Male Coeff. (From Female Regression)	208	0	1.000	-3.485	2.714

3 Results

We start by using time-series variation at the national-level to examine the relationship between Tweets and sexism. The results presented in Panel A of Table 2 indicate that in months with a greater number of Tweets that insulted Clinton, sexist Google searches increased. This is true both over the entire sample (Columns 1 and 2) and in the 16 months leading up to the election (Columns 3 and 4), although the coefficient on the before-election sample is larger and has a lower p-value. In panel B, we replicate the estimations that appear in panel A but use as the independent variable the number of Tweets in a month that insult any woman, excluding Clinton. We find similar results in panels A and B.

We include as a control variable in Columns 2 and 4 Tweets that insult a man and find no evidence that this is correlated with the sexism index. This suggests that the correlation between Tweets that insult women and sexist Google searches is not the result of insulting Tweets generating hostility in general; Tweets that insult women specifically are associated with increased volume of sexist Google searches.

Table 2. Time Series Analysis of Impact of Trump Twitter Insults on Sexism.

	Dependent Variable: Sexism Index			
VARIABLES	(1)	(2)	(3)	(4)
Panel A: Impact of Tweets Insulting Clinton on Sexism				
Tweets Insulting Clinton	0.00227*	0.00229*	0.00509***	0.00581***
	(0.00125)	(0.00126)	(0.00160)	(0.00174)
Tweets Insulting Men		0.000330		-0.00291
		(0.000888)		(0.00279)
Observations	64	64	16	16
R-squared	0.979	0.979	0.907	0.917
Sample	Full	Full	Pre-2016	Pre-2016
Panel B: Impact of Tweets Insulting Women (excluding Clinton) on Sexism				
Tweets Insulting Women	0.00556**	0.00555**	0.00954**	0.00990**
	(0.00233)	(0.00237)	(0.00380)	(0.00410)
Tweets Insulting Men		2.78e-05		-0.00109
		(0.000877)		(0.00309)
Observations	64	64	16	16
R-squared	0.980	0.980	0.885	0.887
Sample	Full	Full	Pre-2016	Pre-2016

Notes: Monthly time-series specifications. All columns include quadratic trends interacted with year fixed effects. Columns 1 and 2 show results on the sample over Jun. 2015-Dec. 2020. Columns 3 and 4 show results on the sample over Jun. 2015-Nov. 2016. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

There is considerable variation across the U.S. in the sexism index and we exploit that variation in the panel analysis that is presented in Table 3. As before, Panel A examines Tweets that insult Clinton and Panel B examines Tweets that insult any woman except Clinton. The use of panel data allows us to include media market fixed effects which should capture the variation in the level of sexism across media markets that is not influenced by factors that vary over this time period. Even after adding media market fixed effects, we obtain similar results to those in the time series analysis in both Panel A and B: increases in Tweets insulting Clinton (or women generally) are associated with an increase in sexist Google searches in both the full panel (columns 1 and 2) and in the sample that is restricted to before the 2016 election (column 3 and 4).

Table 3. Panel Analysis of Impact of Trump Twitter Insults on Sexism.

	Dependent Variable: Sexism Index			
VARIABLES	(1)	(2)	(3)	(4)
Panel A: Impact of Tweets Insulting Clinton on Sexism				
Tweets Insulting Clinton	0.000874***	0.000871***	0.00155***	0.00172***
	(0.000229)	(0.000229)	(0.000313)	(0.000330)
Tweets Insulting Men		-0.000143		-0.000683
		(0.000154)		(0.000422)
Observations	13,691	13,691	3,535	3,535
R-squared	0.727	0.727	0.816	0.816
Sample	Full	Full	Pre-2016	Pre-2016
Panel B: Impact of Tweets Insulting Women (excluding Clinton) on Sexism				
Tweets Insulting Women	0.000856***	0.000867***	0.00127***	0.00144***
	(0.000175)	(0.000175)	(0.000235)	(0.000251)
Tweets Insulting Men		-0.000191		-0.000843**
		(0.000154)		(0.000427)
Observations	13,691	13,691	3,535	3,535
R-squared	0.727	0.728	0.816	0.817
Sample	Full	Full	Pre-2016	Pre-2016

Notes: Monthly panel specifications. All columns include quadratic trends interacted with year fixed effects, and media market fixed effects. Columns 1 and 2 show results on the sample over Jun. 2015-Dec. 2020. Columns 3 and 4 show results on the sample over Jun. 2015-Nov. 2016. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In Table 4, we present the results of the second step of the two-step estimation described above. This estimation links Tweets to election outcomes via their impact on sexism. In these regressions, the media market coefficients from Equation 3 on Tweets insulting Clinton (columns 1 and 2) or Tweets insulting women (columns 3 and 4) are used to predict support for Clinton. For the dependent variable, we difference Clinton's 2016 vote share relative to either Obama's vote share in 2012 (Panel A) or 2008 (Panel B) to account for the possibility that Trump Tweets have a smaller impact in Democratic areas.

The negative and significant correlations in all estimations in Panels A and B indicate that support for Clinton is lower in media markets where Trump Tweets had a larger effect on sexism. Note that all columns control for both differences across census divisions and variation in sexist attitudes, so these results are consistent with a channel through which Tweets activated sexism which then influenced votes. In other words, Clinton had a lower vote share relative to Obama in areas that had a greater response to sexist Trump Tweets, even after controlling for the overall level of sexism in the area. In Panel C, we present evidence from a placebo test in which the dependent variable is the difference in Obama's share of the votes in 2012 vs. 2008. We find no evidence in Panel C that the media market coefficients are correlated with these election outcomes, giving us further confidence that the results in Panels A and B identify a channel through which sexism was activated in a politically consequential way.

Table 4: Impact of Tweets on Election via Sexism

VARIABLES	(1)	(2)	(3)	(4)
	Panel A — Dependent Variable: %Clinton2016 - %Obama2012			
Clinton/Female Coefficient	-0.00747*	-0.00909**	-0.00729*	-0.00896**
	(0.00409)	(0.00425)	(0.00395)	(0.00408)
Male Coefficient		0.00898**		0.00900**
		(0.00373)		(0.00372)
Observations	203	203	203	203
R-squared	0.390	0.409	0.389	0.408
Coefficient from first stage	Clinton	Clinton	Female	Female
	Panel B — Dependent Variable: %Clinton2016 - %Obama2008			
Clinton/Female Coefficient	-0.00963**	-0.0113**	-0.00909**	-0.0108**
	(0.00430)	(0.00440)	(0.00422)	(0.00429)
Male Coefficient		0.00935**		0.00931**
		(0.00375)		(0.00376)
Observations	203	203	203	203
R-squared	0.444	0.459	0.442	0.457
Coefficient from first stage	Clinton	Clinton	Female	Female
	Panel C — Dependent Variable: %Obama2012 - %Obama2008			
Clinton/Female Coefficient	-0.00247	-0.00235	-0.00196	-0.00182
	(0.00156)	(0.00158)	(0.00147)	(0.00149)
Male Coefficient		-0.000598		-0.000708
		(0.00163)		(0.00163)
Observations	204	204	204	204
R-squared	0.278	0.279	0.275	0.276
Coefficient from first stage	Clinton	Clinton	Female	Female

Notes: Specifications at the media market level. All columns include census division fixed effects and control for an area's sexism index. Columns 1 and 2 include as an independent variable the coefficient from regressing sexism on Tweets insulting Clinton. Columns 3 and 4 include as an independent variable the coefficient from regressing sexism on Tweets insulting women other than Clinton. Bootstrapped standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Our interpretation of these results is that Trump Tweets inflamed sexism in a way that influenced votes. Of course, an alternative explanation is that people who had already decided to vote for Trump were following his Tweets more closely and, therefore, more likely to express sexism online when he Tweeted insults at women. While this would still be an interesting result that suggests an important role for social media in generating anti-social behavior, it would not be consistent with our interpretation that the Tweets impacted votes. To address this concern, we present in Table 5, further placebo tests in which Trump's opponent was a man. Specifically, we use the same estimates of sensitivity to Trump Tweets that we use in Table 4, but instead of predicting Clinton's share of the vote relative to Obama, we predict Biden's share. If people who are already Trump supporters are the people who are responding to his Tweets with sexist searches, then we should find similar patterns in the 2016 and 2020 elections. However, the insignificant results in Table 5 cast doubt on this alternative explanation.[3] Taken together, our results suggest that the

[3] In unreported results, we also test if the impact of Tweets differed after Trump won the nomination and garnered more attention and support. We find that it did not.

Tweets insulting Clinton or other women inflamed sexism and that this sexism led people who would have otherwise voted for a male Democrat to switch their votes to Trump.

Table 5 Placebo Test: Impact of Tweets via Sexism on Election between Two Men

VARIABLES	(1)	(2)	(3)	(4)
	Panel A — Dependent Variable: %Biden2020 - %Obama2012			
Clinton/Female Coefficient	0.00459	0.00273	0.00497	0.00310
	(0.00534)	(0.00583)	(0.00491)	(0.00538)
Male Coefficient		0.00847		0.00838
		(0.00551)		(0.00553)
Observations	178	178	178	178
R-squared	0.262	0.280	0.263	0.281
Coefficient from first stage	Clinton	Clinton	Female	Female
	Panel B — Dependent Variable: %Biden2020 - %Obama2008			
Clinton/Female Coefficient	0.00297	0.00126	0.00397	0.00228
	(0.00535)	(0.00579)	(0.00496)	(0.00536)
Male Coefficient		0.00783		0.00760
		(0.00483)		(0.00483)
Observations	178	178	178	178
R-squared	0.350	0.364	0.352	0.364
Coefficient from first stage	Clinton	Clinton	Female	Female

Notes: Specifications at the media market level. All columns include census division fixed effects and control for an area's sexism index. Columns 1 and 2 include as an independent variable the coefficient from regressing sexism on Tweets insulting Clinton. Columns 3 and 4 include as an independent variable the coefficient from regressing sexism on Tweets insulting women other than Clinton. Bootstrapped standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Finally, we perform calculations for the magnitude of the impact. For the median media market, the estimations reported in Column 1 and Panel A of Table 4 indicate that a one standard deviation increase in the media market coefficients for Tweets insulting Clinton is associated with a decrease in Clinton vote share relative to Obama in 2012 of 0.795 percentage points. Given the margins by which Trump won the election, this magnitude is meaningful.

4 Conclusion

Previous authors have shown that individuals and areas that expressed greater levels of sexism were more likely to vote for Donald Trump. We add to the analysis of sexism and the 2016 presidential election by showing that expressions of sexism increased in response to Tweets by Trump that either insulted his female opponent or Tweets that insulted any woman. Overall, we show that 1) sexist Google searches increased in the months in which Trump Tweets insulted women, 2) there is variation in the responsiveness of sexist Google searches to Trump Tweets across media markets, and 3) this variation in sensitivity to

Trump Tweets is correlated with Clinton's share of votes relative to Obama's, even after controlling for overall levels of sexism in the media market. In other words, the additional sexism associated with Trump Tweets is correlated with election outcomes.

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