Women's Wave or the Blue Wave? Results from the 2018 U.S. House Elections*

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Abstract

This paper tests the connection between the MeToo movement and the 2018 midterm elections. The empirical strategy exploits the 2018 MeToo tweets that can be matched to U.S. counties. Using a difference-in-differences specification at the house candidate and district-county level, the findings are nuanced. The expected advantage for Democratic women and disadvantage for Republican men is observed only in places with high existing Republican support. Further tests suggest that turnout is a primary channel for this effect, and that the intensive margin in the movement—how much individuals are tweeting about the movement given that they do tweet—is what really matters for the mobilisation.

1 Introduction

The 2018 U.S. midterm elections—which took place during the peak of the MeToo movement—saw women candidates achieve historic gains. These elections took place halfway through the first term of Republican President Donald Trump when Republicans held a majority in both the House of Representatives and the Senate. In the House, all 435 seats were up for election and the Republicans lost 40 seats—the most since the 1974 midterm elections.[1] Overall, the 2018 midterms have the highest number of women candidates voted into Congress. The House in particular, had 235 women candidates, with 102 of them winning, and most (89) running under the Democratic banner (Center for American Women and Politics 2018). In this paper, I test the assertion that the 2018 election was a "MeToo election".

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[1] The Democrats gained a net of 49 seats in the 1974 post-Watergate House elections.

To test whether the house Republican candidates incurred a backlash from the MeToo movement, I first download all tweets containing the MeToo hashtag in the year 2018, leading right up to the general elections on Nov 6. I then match the tweets to U.S. counties using the twitter user geolocation. This county-level variation in tweets is the measure of the MeToo movement.

The empirical strategy uses the difference-in-differences approach by comparing the electoral performance of U.S. house candidates across counties and across parties (and gender). This approach mitigates concerns that candidates select into districts, such as Democratic or women candidates competing only in or campaigning harder in districts with high support of the MeToo movement.

The findings are nuanced. It turns out that the expected advantage of Democratic women candidates and the disadvantage for Republican men occurs only in Republican strongholds, where there is a high Republican vote share in the 2016 presidential elections. Given a standard deviation increase in the republican presidential vote share, a standard deviation increase in the tweet density measure is associated with a 0.96 percentage point advantage for Democratic women candidates, while the Republican men incur a 0.45 percentage point disadvantage. As validation of the tweets measure, I use microdata from a new survey to confirm that the tweets are highly correlated with the pro-women and anti-Republican sentiment of their county residents.

There are three main interpretations of the results. First is the possibility that women candidates select into Republican districts with a high prevalence of the MeToo movement. Below, I show that neither the Republican vote share nor the tweets can predict the presence of a woman candidate. A second interpretation is that the tweets, and the MeToo movement, is a signal of the intent to turn out to vote women or Democratic . In this sense, voters were already planning to vote for women and the Democrats in those Republican counties with a high incidence of the MeToo tweets, which cannot be ruled out using the data.

The third interpretation is that the movement, as measured by the tweets, had a mobilising effect on voters in the Republican counties. The results from turnout support this. Using the district-county level changes in House turnout from 2016 to 2018, the estimate suggests that for a standard deviation increase in the log tweet intensity, every 10 percentage point increase in the 2016 presidential Republican vote share increases turnout by 1.17%. This trend cannot be replicated with the previous elections.

The insights by Campante et al. (2017) are consistent with the results here. They use data in Italy and find that when internet diffusion started facilitating local online grassroots protest movements around 2008, parliamentary election turnout increased. Furthermore, the new Italian political party M5S, which itself grew out of those online grassroots movement, is overrepresented by supporters who did not vote in the previous elections. This is consistent with the MeToo movement mobilising voters to turn out to vote for the women and Democratic candidates into the House which, while not as prestigious as the Senate, is the legislative body subject to a two-year election cycle and is thus more responsive to their constituency needs and the grassroots.

This study relates to the literature on the political economy of the mass media, specifically those that look at how varying access to media outlets, and the varying political coverage by the media can affect electoral outcomes (Adena et al. 2015; Boas and Hidalgo 2011; DellaVigna and Kaplan 2007; Enikolopov et al. 2011; Ferraz and Finan 2008; Gentzkow 2006; Larreguy et al. 2014; Lim et al. 2015; Miner 2015; Oberholzer-Gee and Waldfogel 2009). In these studies, the variation from the media comes mostly from changes that are already politically motivated, such as changes in radio broadcasting from the reign of the Weimar government to the Nazi party (Adena et al. 2015), and how the media coverage of malfeasant incumbents affected their vote share (Ferraz and Finan 2008; Larreguy et al. 2014).

A novel feature of this study is how it documents social media influence, arising from what is essentially a grassroots movement, on the House elections. This, as opposed to the influence of more traditional media outlets such as print (Lim et al. 2015), radio (Adena et al. 2015; Boas and Hidalgo 2011; Ferraz and Finan 2008; Larreguy et al. 2014), and broadcast (DellaVigna and Kaplan 2007; Oberholzer-Gee and Waldfogel 2009). Further, the grassroots aspects of the MeToo movement mean that the measures are not directly influenced by political candidates.[2]

Another contribution is on how an independent media platform influences electorate behaviour against the incumbent (Enikolopov et al. 2011; Miner 2015). Miner (2015) finds that the rise of internet access in Malaysia accounted for a large drop in points for the 40-year incumbent party during the 2008 elections. Enikolopov et al. (2011) find that differential access to the only independent national TV channel decreased the Russian government party's vote share during the 1999 parliamentary elections. Neither the internet nor the independent TV channel are centrally con-

[2] Unlike in Boas and Hidalgo (2011) for example, where incumbents have an advantage in gaining access to community radio before elections, which increases their vote share.

trolled nor have a formal political allegiance. The setting in this paper is similar, where the MeToo movement started as an independent grassroots movement. This paper also contributes to a growing literature on the effects of protest movements, including the study by Campante et al. (2017) and the Arab Spring by Acemoglu et al. (2018).

This paper also bears some indirect non-experimental evidence of expressive voting, a behaviour that does not originate from the belief that the vote is instrumental in the election outcome (Fischer 1996; Tyran 2004; Hillman 2010). Another related paper is Stephens-Davidowitz (2014) who uses racial animus proxied using Google search data and finds that Obama did comparably worse than his Democratic peers by vote share in places with higher racial animus.

Finally, the paper contributes to the literature on how access to media sources can influence voter turnout (Campante et al. 2017; DellaVigna and Kaplan 2007; Enikolopov et al. 2011; Gentzkow 2006; Oberholzer-Gee and Waldfogel 2009), and the literature on media bias (Gentzkow and Shapiro 2010; Groseclose and Milyo 2005; Larcinese et al. 2011), with the implicit assumption that a politically biased media sways voter decisions. In the context of this paper, the MeToo movement in social media became overtly pro-Democratic, and one interpretation is that the movement persuaded voters to turn out to vote for the women and Democratic candidates.[3]

The rest of the paper is as follows. The next Section 2 describes the matching of twitter data to U.S. counties. Section 3 discusses legal and political implications of the MeToo movement. Section 4 discusses the empirical strategy and presents the results at the candidate level. Section 5 validates the tweets measure and explores channels of the effect. Section 6 concludes.

2 Data

Getting historical tweets data. I use a third-party custom-written Python library *GetOldTweets-python*[4] to download all tweets containing the "MeToo" hashtag in

[3] Another contribution is that this paper bears some evidence on ethnic and gender-based voting (Abrajano and Alvarez 2005; Flanagan 2018; Holli and Wass 2010; Matsubayashi and Ueda 2011). In this paper, the interactions of county ethnic percentage makeup and candidate (predicted via name) ethnic are systematically correlated to vote share, though the variation it explains in vote share is small.

[4] The *Get Old Tweets* library is written by Jefferson Henrique, and is hosted at `https://github.com/Jefferson-Henrique/GetOldTweets-python`. Two lines of code are changed to handle current changes in the underlying browser's HTML formatting so that the Twitter username can be re-

2018, leading up to the elections on November 6. The total number of tweets found in this period with the MeToo hashtag is 1'915'322.[5]

Geolocation of Twitter users. The tweets metadata include usernames, which I use to query the Official Twitter API for the users' geolocation. The 1'915'322 tweets come from 700'891 usernames. Of the 700'891 usernames, 158'857 cannot be found through the Twitter API at the time of query, and another 21'521 users can be found but the geolocation string is left empty. For the remaining 520'513, I obtain the Twitter users' geolocation tagged to the account. This disclosure of geolocation by users is tagged to their user account and is completely voluntary and without standardised formatting. To parse the er geolocation strings I write a series of hard-coded rules to identify U.S. city-state, if applicable. This allows me to successfully parse 130'433 (25% of 520'513) geolocations into a standard city-state (e.g. Grand Rapids, Michigan). Finally, I match the city-states to their primary counties using the *United States Cities Database*,[6] where primary counties are the centroids of the city as defined by the U.S. Geological Survey. Appendix A.1 provides more details.

2018 House election data. The primary source for the 2018 House of Representatives election returns comes from the individual states' Secretary of State. I hand-collect the returns of individual candidates at the county-level using their Election Department's report. From this, I collect data on 40 states. I supplement data on 4 more states (Arkansas, Michigan, Nevada, and New Mexico) using the *MIT Election Data and Science Lab*'s unofficial results.[7] [8] For the individual political candidates, I also record gender and incumbency. I infer candidate race (or ethnic) using their names (both first and last) through the *NamePrism* API (Ye et al. 2017). From this, each of the 1'022 candidates has an indicator for whether their (predicted) ethnic is White, Black, Hispanic, or Others.[9]

trieved. The Official Twitter API has a 7-day limit on past tweets at the time of this writing.

[5] Under the hood, the third-party API scrapes the Twitter Search which allows users to find historical tweets containing certain keywords. Search results appear in a scroll loader which loads more tweets through calls to a JSON provider as a user continues scrolling down, without a definite limit.

[6] https://simplemaps.com/data/us-cities

[7] https://github.com/MEDSL/2018-elections-unoffical.

[8] At the time of collection, Alaska's Secretary of State (SOS) page on election results cannot be found, Connecticut, Kansas, Mississippi, and Missouri SOS page lacks voting results at the county or precinct level, and Minnesota has yet to publish their election results.

[9] The NamePrism is a supervised classifier developed using 74 million names from an email company. Their Naive Bayes classifier infers nationality/ethnicity using both first and last names (to mitigate migration and marriage), with the likelihood estimated using the homophily principle in communication pattern—people of the same type communicate more frequently and recently.

[10] *January 7* Golden Globe awards; *January 20* a million people took part in the second annual Women's March on the anniversary of President Donald Trump's oath of office, voicing disapproval

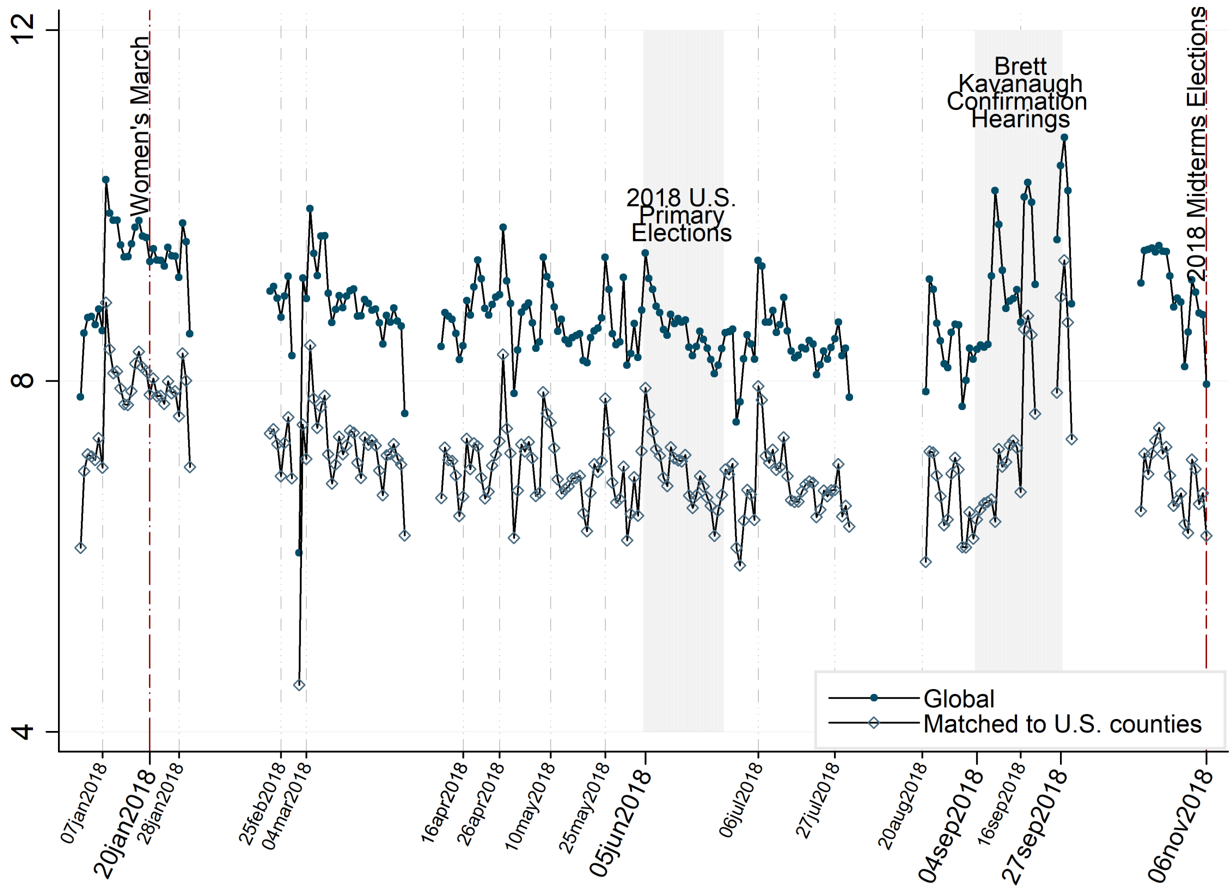

Figure I: Intensity of Tweets with MeToo Hashtag in 2018[10]

County-level covariates. County demographics come from the ACS (American Community Survey) 5–year estimates for 2012–16. The 14 variables include population and voting population sizes, demographic composition by ethnicity, gender, age, foreign-born, and education, income and unemployment data, and the rural-urban distribution. County-level density measure of high-speed internet connection—computed as the ratio of the number of residential units with at least 200 kbps in at least one direction to the total number of households—for June 2017 come from the FCC (Federal Communications Commission)[11] For past elections, both the county-

of his administration and encouraging people to vote; *January 28* Actor Jeremy Piven accused of sexual assault by three more women; *February 25* Monica Lewinsky writes an essay about her experience with Bill Clinton; *March 4* Oscars; *April 16 The New York Times* and *The New Yorker* won the *Pulitzer Prize* gold medal for public service for their work on the Harvey Weinstein scandal and sexual assault in general; *April 26* Bill Cosby finally found guilty of sexual assault; *May 10* Spotify no longer plays R. Kelly; *May 25* Harvey Weinstein is taken into police custody; *June 5* 17 states have their primary elections; *July 6* Canada PM Justin Trudeau denies need to conduct investigation of sexual misconduct against him; *July 27* a *New Yorker* article reports that CBS will investigate allegations of sexual misconduct by its CEO Leslie Moonves; *August 20* accuser Asia Argento herself accused of sexual misconduct; and *September 16* a *Washington Post* article revealed Christine Blasey Ford was a victim of sexual assault by then Supreme Court nominee Brett Kavanaugh. See for example https://www.chicagotribune.com/lifestyles/ct-me-too-timeline-20171208-htmlstory.html for a curation of MeToo events.

[11] https://www.fcc.gov/general/form-477-county-data-internet-access-services.

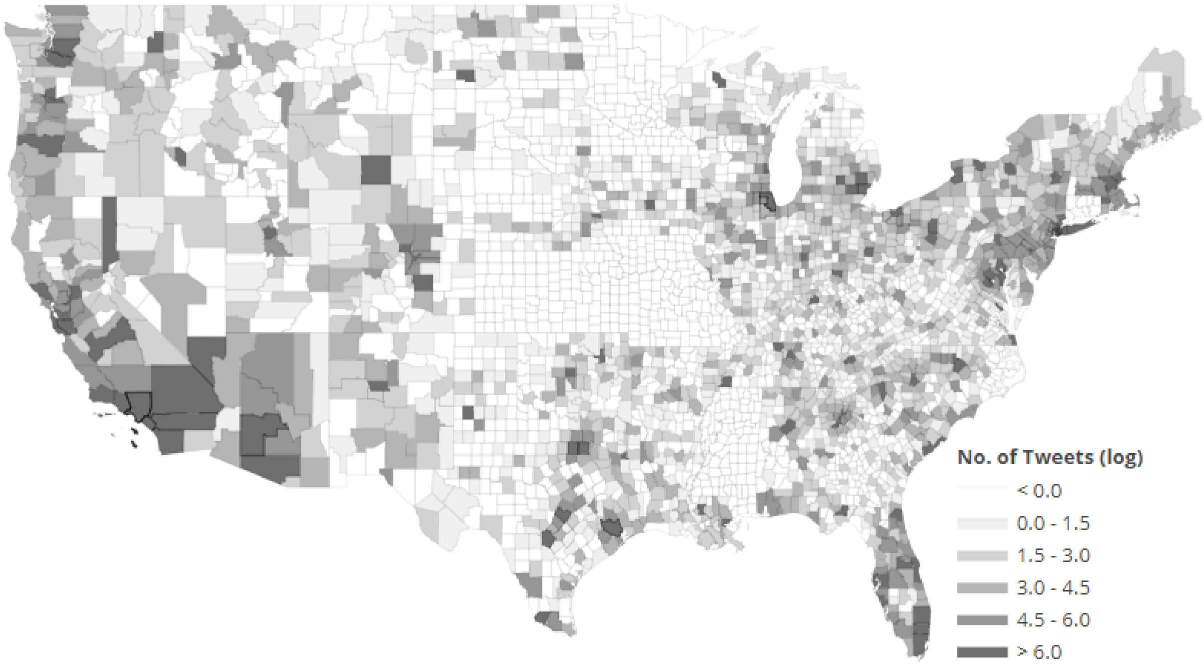

Figure II: Geographical Distribution of MeToo Tweets in 2018

level 2016 House elections and Presidential elections data come the *MIT Election Data and Science Lab*.

Summary. Figure I shows the intensity of the MeToo tweets throughout the year 2018 right up to the election on the 6th of November. I make two observations here. First, is that the intensity of the tweets is relatively consistent throughout, without a single salient spike. In fact, a few spikes occur which can be traced to a number of identifiable events such as the Cosby hearing and the (second) Kavanaugh confirmation hearing. The second observation is that even though the geolocations of Twitter users cannot all be parsed into identifiable U.S. counties—some because they are unambiguously outside the U.S.—the plot shows that the time trend of the global tweets and the identifiable U.S. counties tweets are similar, suggesting that there is no systematic difference in the tweets that can and cannot be matched to U.S. counties. Figures II and III provide insight into the geographical variation in the MeToo tweets intensity (logs) and vote share of the political candidates. There is substantial geographical variation in the tweets and the vote share of candidates, by both state and county.

The final sample is for 44 U.S. states, with 388 House congressional districts, 2'652 counties, and 1'022 House election candidates, of which 767 are from the two main parties. This gives 8'653 candidate-county-level observations. Districts, where a single candidate wins by default, are not included in the sample.

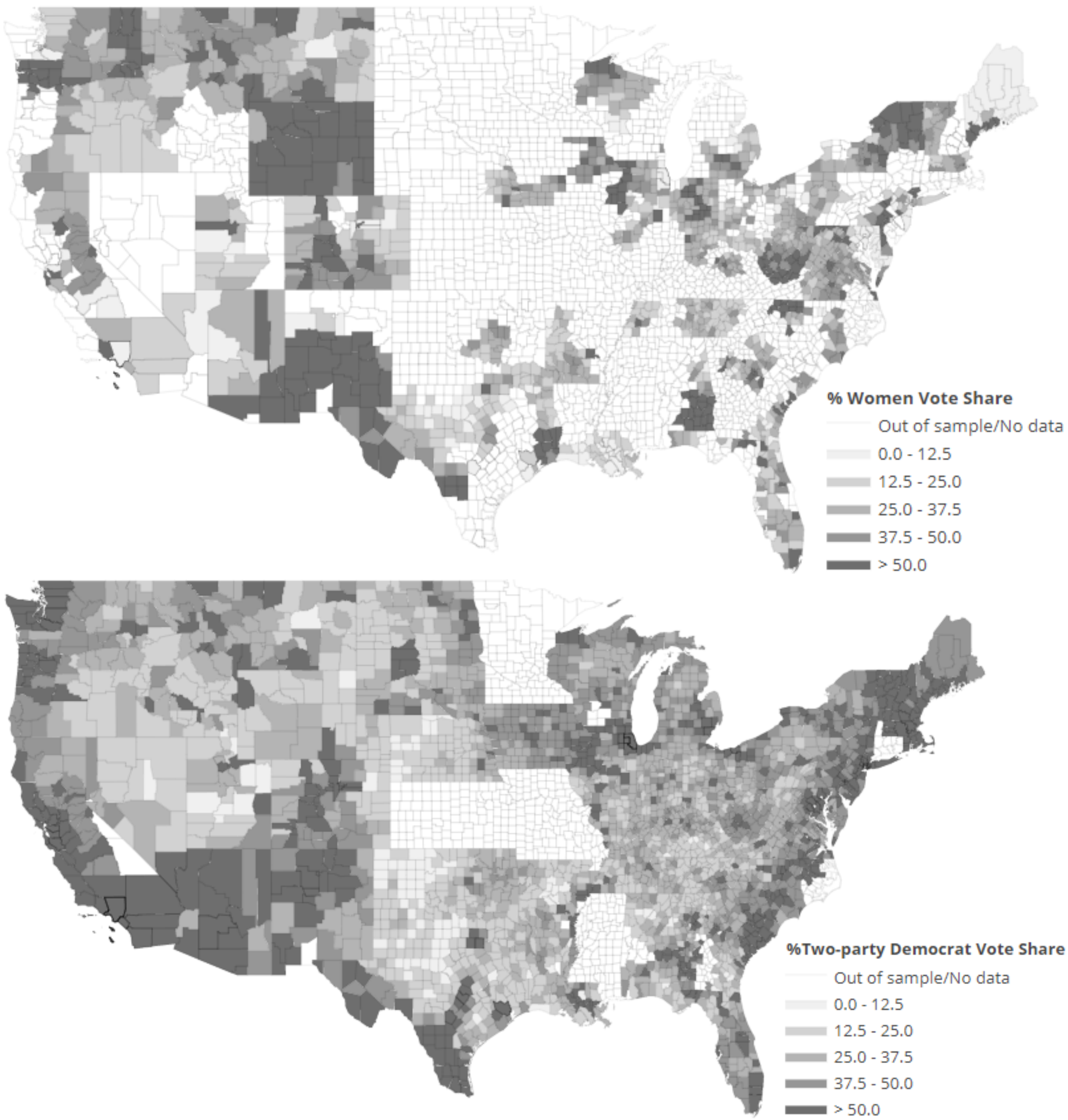

Figure III: Geographical Distribution of Women and Democratic Vote Share

3 Background

The MeToo Movement. The phrase "Me Too" began more than a decade ago in 2006 on the myspace social network, when Tarana Burke used it in her local community to encourage Black and Hispanic girls, as well as other women to come forth with their accounts of sexual misconduct (Gibson et al. 2019). Social media became the place where these accounts can be made available to the mass public, and the MeToo movement picked up massive momentum in 2017 when celebrities lent their voices and experiences, notably on the microblogging and social networking service Twitter. Tweets of this nature use the MeToo hashtags.

Legal Implications of the Movement. The MeToo movement, with widespread attention in social media, is more than just window dressing. First, the attention on sexual harassment issues have gained traction in Congress, with Democrats sponsoring the BE HEARD Act[12] with bipartisan support to extend harassment protections to workers at small businesses and independent contractors (North 2019).[13] Second, courts tended to apply the *Faragher* defense—when employers can show they took reasonable measures to prevent or redress harassment—in favour of employers, and the MeToo movement may pressure courts to be more narrow on what they consider reasonable.[14] Third, some states (including California, New York, and Pennsylvania at the time of writing) are considering or have already passed bills to limit the extent of non-disclosure agreements, including its use in cases of sexual misconduct.[15]

Fourth, at least two judges—Judge Aaron Persky in California and Judge Michael Corey in Alaska—at the time of writing have been recalled as a reaction to their lenient sentencing of specific sexual assault cases in 2018, in spite of favourable judicial performance evaluation.[16] The recall campaigns ride on the MeToo movement and the contemporaneous controversy surrounding the confirmation hearings for Supreme Court nominee Brett Kavanaugh, which was itself tangled with the movement. Before this, the most recent recall of a state judge went back to 1977 (Singer 2019).[17] [18]

Electoral Implications of the Movement? The media in particular, has framed the 2018 midterm elections as a "#MeToo election", asserting that women candidates will benefit from the movement.[20] Figure IV shows the jump in both women candidates running and voted into Congress in the 2018 elections, affirming the fact that the 2018 elections are historic for the representation of women in Congress.

Another possibility is that Democratic candidates benefit since the MeToo move-

[12] Bringing an End to Harassment by Enhancing Accountability and Rejecting Discrimination Act

[13] Under Title VII of the Civil Rights Act, there is no explicit reference to harassment, and courts generally treat issues of sexual harassment as a form of discrimination (Tippett 2018).

[14] Tippett (2018).

[15] Tippett (2018).

[16] Singer (2019).

[17] In states with the retention election system, nonpartisan commissions nominate qualified judicial candidates to the governor, who then appoint a nominee to an open seat. Appointed judges then face periodic retention elections without another challenger, the only decision voters have to make is whether to retain or recall the judge. Some states have judicial performance evaluations in place for these elections so that the electorate can make informed decisions (Singer 2019).

[18] In a similar turn of events, former Connecticut U.S. house representative and Democrat Elizabeth Etsy was publicly pressured to resign, after it became known that she attempted to cover up sexual misconduct by her chief of staff. She retired and the vacated seat was later won by Democrat Jahana Hayes, the first Black woman to represent Connecticut in Congress. See for example https://edition.cnn.com/2018/03/30/politics/elizabeth-esty-staffer-abuse/index.html.

[19] Center for American Women and Politics (2018).

[20] Deckman (2018) drew links months before the elections, and Peaker (2018) after.

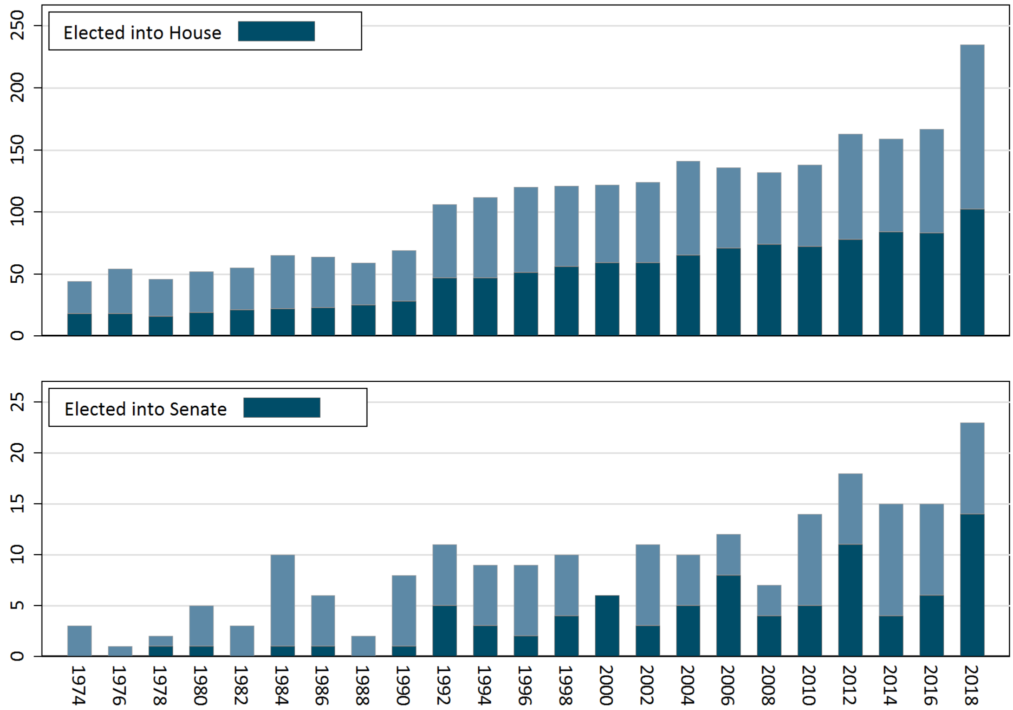

Figure IV: Women in Congress[19]

ment became tied to partisan attitudes. The nomination and confirmation hearings of Kavanaugh was a particularly salient politically charged episode.[21] In fact, from the timeline of the MeToo movement from Figure I, the peak as reflected on Twitter came right after the second hearing. The incumbent Republican President Trump himself, accused of sexual harassment, is a subject of the movement. There were women marches shortly after the 2016 Presidential election as an objection to Trump's election.[22] Figure V suggests this (negative) correlation between the MeToo movement and the house Republican vote share.

3.1 Determinants of Tweet Density by County

I first check if past and existing trends can determine the intensity of the MeToo tweets in 2018. The full model I estimate is:

$$\tau_c = \alpha + \boldsymbol{\beta}_1 \boldsymbol{\nu}_{c,\ 2016}^{\text{Rep., House}} + \boldsymbol{\beta}_2 \boldsymbol{\nu}_{c,\ 2012-16}^{\text{Rep., Pres.}} + \boldsymbol{\Gamma} \boldsymbol{X}_c + \varepsilon_c, \tag{1}$$

where τ_c is log county-level tweet density—the number of (identified) county-level MeToo tweets in 2018 (before the elections) divided by county population. $\boldsymbol{\nu}_{c,\ 2016}^{\text{Rep., House}}$ are the 2016 house Republican vote share and turnout, $\boldsymbol{\nu}_{c,\ 2012-16}^{\text{Rep., Pres.}}$ are the 2012–16 equivalent, and $\boldsymbol{X}_c$ are the county census variables. Standard errors are clustered

[21] See for example the media piece by Walsh (2018).
[22] See note 10.

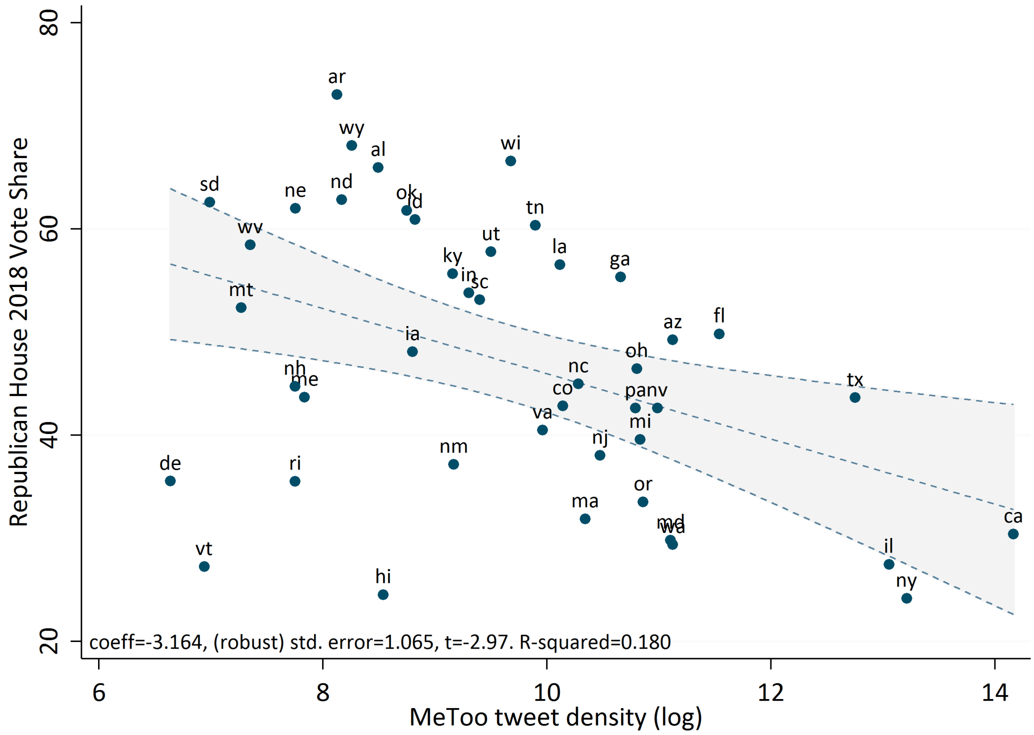

Figure V: Republican Vote Share and MeToo Movement

at the congressional districts.

Column (1) of Table II includes only the full interaction of county high-speed internet connection density and percentage females as a control, which is positively correlated with the MeToo movement. Column (2) includes controls for the 2016 House election and presidential election outcome. The previous link between internet connection and percentage disappears, but the Republican vote shares on the other hand are statistically significant. I interpret this as an indication that the movement is predominantly political rather than gender-based.

Column (3) adds the county census demographics, which are highly correlated with tweet density, as anticipated and indicated by the joint F-statistic. This is likely because urban areas and education are highly correlated with the MeToo movement. I show below however, that accounting for these demographics does not change the main results.

Column (4) adds the congressional district fixed effects. With this, the estimates capture within-district determinants of the MeToo tweet density in the year 2018, leading up to the elections. Turnout in the 2016 presidential election is now positively associated with the tweets measure ($\rho < 0.05$). The Republican vote share in the 2016 House and presidential elections however, is no longer significant, indicating that the county-level MeToo tweets are not correlated with the past election results within the House congressional districts themselves. Column (5) uses the two-party Republican vote share measures (votes received by Republican candidates divided by votes received by both Republican and Democratic candidates), and the results are similar.

3.2 Selection of Women Candidates into Districts

In Table A2, I also check what covariates are linked to the presence of women candidates for the 388 U.S. congressional districts in the sample. Specifically, the model I estimate is:

$$I_{ds} = \alpha + \beta\tau_d + \mathbf{\Gamma}\boldsymbol{X}_d + \mathbf{\Delta}\boldsymbol{Z}_d + \text{state}_s + \varepsilon_{ds}, \tag{2}$$

where I is the dummy for the presence of women candidates at the districts; τ_d is the district-level log tweet density; $\boldsymbol{Z}_d$ are dummies for whether the seat is open, has a woman incumbent, or has a Republican incumbent; $\boldsymbol{X}_d$ are all other district-level controls including the aggregated county census controls and past electoral trends. All regressions include state fixed effects, with standard errors clustered at the 44 states in the sample.

Assuringly, the selection of women candidates is orthogonal to the occurrences of the MeToo tweets and past electoral trends in both the House and the Presidential elections. Strong predictors (both economically and statistically) of women challenging incumbents come from the political seat characteristics. Women are more likely to challenge when the seat is open, and when the incumbent is Republican ($\rho < 0.01$).[23]

4 Empirical Results

4.1 Empirical Strategy

To identify the effect of the MeToo movement on the 2018 House elections, the baseline empirical strategy I use is the difference-in-differences (DD) strategy, comparing the vote share of individual candidates across counties, which vary in their intensity and density of the MeToo tweets. Specifically, I regress the vote share of

[23] The MeToo tweets measure also does not predict whether a district has specifically a Democratic woman challenger, nor does the interaction of tweets and Republican vote share predict the presence of women challengers.

individual candidates at the district-county level,[24] on the interaction of candidate party, gender, and the density of the MeToo tweets at the county levels:

$$\text{(3)} \quad \nu_{icd} = \alpha + \beta^{RW} RW_i\tau_c + \beta^{DW} DW_i\tau_c + \beta^{RM} RM_i\tau_c + \beta^{DM} DM_i\tau_c + \text{Candidate}_i + \mathbf{\Delta}_1 \boldsymbol{\nu}^{\text{Rep., House}}_{c,2016} + \mathbf{\Delta}_2 \boldsymbol{\nu}^{\text{Rep., Pres.}}_{c,2012-2016} + \mathbf{\Gamma} \boldsymbol{X}_{ic} + \varepsilon_{icd},$$

where ν_{icd} is the vote share of 2018 house candidate i in district-county cd; τ_c is the county-level log of tweet density (county MeToo tweets divided by population); where R (or D) indicates candidate from the Republican (Democratic) party, and W (or M) indicates a woman (man) candidate, so that RW for instance, indicates a Republican woman candidate. So if there is indeed an advantage for the Democratic women candidates in counties with high incidences of the MeToo tweets, then $\beta^{DW} > 0$.

The full specification includes the interaction of candidate party and gender with past electoral outcomes. $\boldsymbol{\nu}^{\text{Rep., House}}_{c,2016}$ is the full interaction of the 2016 house Republican vote share and candidate party; and $\boldsymbol{\nu}^{\text{Rep., Pres.}}_{c,2012-2016}$ is the full interaction of the 2016 presidential Republican candidate vote share and candidate party. This prevents the DD estimates from picking up existing political support for the parties. The full sample regressions also include the dummy interaction for all third-party candidates.[25]

The vector $\boldsymbol{X}_{ic}$ are the county census demographics which enter as full interactions with candidate party. This prevents the DD estimates from capturing how votes differ by the basic demographics (Edlund and Pande 2002; Herron and Sekhon 2005; Oswald and Powdthavee 2010). $\boldsymbol{X}_{ic}$ also includes the interaction of candidate ethnic (African American, Hispanic, Others, and White) with the percentage composition of the corresponding ethnic at the county level, and similarly with gender. This allows for voting heuristics, where voters cast their ballot based on the ethnicity or gender of the candidates (as in Abrajano and Alvarez 2005; Holli and Wass 2010; Stephens-Davidowitz 2014; Flanagan 2018).

The baseline specification (3) includes candidate fixed effects, which removes county-invariant candidate characteristics, including party, incumbency, and open seat contests. The candidate fixed effects also prevents the DD estimates from picking up past private and public office credentials, seniority in committees, as well as campaigning and overall support in a district. The standard errors are clustered by candidates.[26]

[24] Some districts have boundaries that run across counties.
[25] Coefficients for third-party candidates not reported to conserve on space.
[26] In an appendix robustness check in Table A4, using non-nested two-way clustering of standard

In what scenarios would the DD estimates be biased? An important identifying assumption in the DD specification (3) is that candidate campaigning across counties of a district are uniform. And, if there are heterogeneities in campaigning across counties, then they must be orthogonal to candidate party (gender) or to the prevalence of the MeToo movement at the county level. That is, Democratic or women candidates are not just campaigning harder in geographical areas with a higher level of interest in the MeToo movement, as proxied by the MeToo tweets in 2018.

The results will also be biased if the MeToo tweet density captures the intent to vote for women candidates, and that women candidates only run in districts with high occurrences of the tweets. I show in Table A2 however, that the tweets are orthogonal the presence of women candidates in districts. Moreover, the DD specification identifies within rather than cross-district variations. The remaining assumption is that women (Democratic) candidates are not selecting into districts with high variation of the MeToo movement, while the men (Republican) candidates are simply selecting into districts with low variation, but where the aggregated district measure of tweet density for both the women and men (Democratic and Republican) are statistically identical. I find this selection behaviour unlikely.[27]

Another form of bias comes from a few layers of measurement errors. First, tweets containing a MeToo hashtag in 2018 are only a proxy for how engaged county citizens are in the MeToo movement. Further, the engagement can go in either direction—pro-feminist or anti-feminist—though I show below that the tweets do proxy for the expected pro-feminist direction. Second, the MeToo tweets is itself measured with error, since only a subset of the global tweets (twitter users) can be successfully matched to US counties, and some days have missing records (Figure I). Finally, the twitter user geolocation record might itself be inaccurate, since a user may no longer (or have never) reside in the reported area. All these work against the results, reducing the precision of the estimates.

4.2 Average Effect on Candidate Vote Share

Columns (1)–(2) of Table III reports the results from estimating equation (3). All reported coefficients are in absolute terms.[28] In column (1), only the DD estimates for

errors for the house candidates and county does not change the results.

[27] In an appendix robustness check in Table A4, I show that excluding districts where the within district variation in the MeToo tweets is less than the 90th percentile does not change the results.

[28] So that the coefficients can be interpreted without requiring back-of-envelope differencing/addition The full report of the three-way interaction between candidate party-gender, log tweet density,

candidate party gender and candidate fixed effects are included ($\Delta_1 = \Delta_2 = \Gamma = 0$ in equation (3)), and the estimates are as anticipated, suggesting that the movement had an effect by both candidate party and gender lines. Democratic candidates have an advantage in counties with high MeToo tweet density, while both Republican candidates face a disadvantage. The DD estimate for Democratic women in particular, imply they get a 2.4 percentage point advantage with a standard deviation increase in the tweet density measure (1.164), while the Republican men get a 2.6 percentage point disadvantage.

Column (2) enters past electoral controls and county demographics as full interaction with candidate party, together with a set of controls for ethnic and gender-based voting. In this most demanding specification, the average effect of the MeToo tweets on candidate vote share by party and gender disappears. In addition, the F-tests for ethnic and gender voting are highly significant, suggesting that there is a strong statistical tendency for voters to vote along their own gender and party line, even if the overall variation it explains in candidate vote share is small.[29]

The average effects in columns (1)–(2) of Table III however, might hide heterogeneous effects. Since the MeToo movement is linked to partisan attitudes, and in particular that the MeToo movement is highly linked to the disapproval of the Republican party (in its handling of sexual harassment issues), I test below whether there is a backlash of Republican candidates in Republican strongholds.

4.3 Heterogeneous Effect/Backlash, by Existing Republican Support

The conditional plot in Figure VI provides visual indication to a heterogeneous effect of the MeToo movement, where the three binned scatters are for Republican vote share between 0%–50%, 40%–60%, and 50%–100%. The anticipated disadvantage of Republican candidates in the 2018 House elections comes only in counties with high Republican vote share ($> 50\%$) in the 2016 Presidential election.

To test this formally, I add the 2016 presidential Republican vote share to the above interaction of party-gender and log tweet density. The full specification, with

and the 2016 presidential Republican 2016 vote share is in Table A3.

[29] The result does not change with the main-party sample.

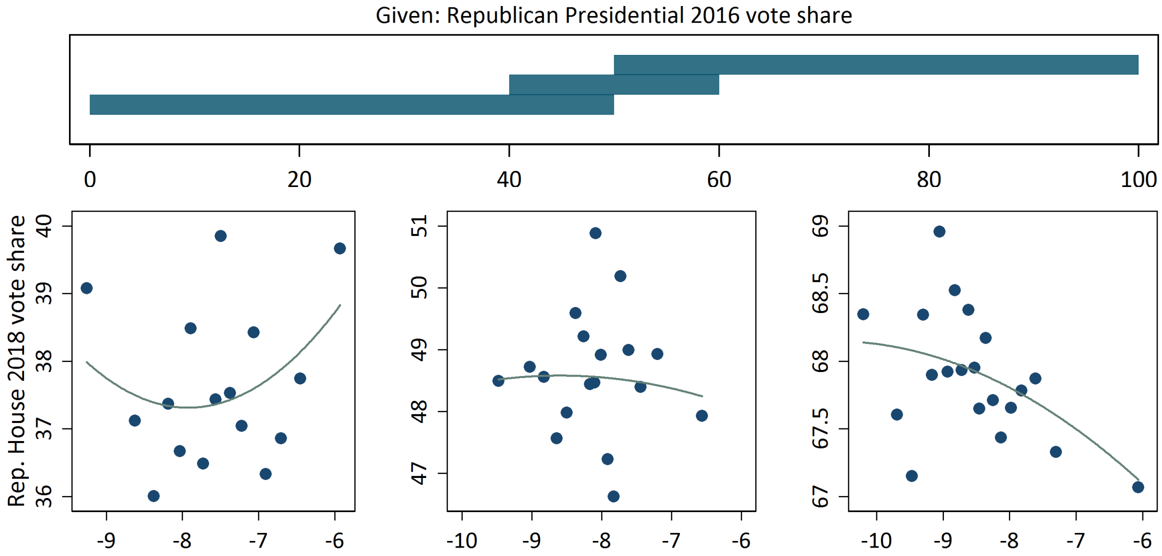

Figure VI: Conditional Effect of MeToo Movement[30]

absolute effects for ease of interpretation, is:

(4)

$$\begin{aligned}\nu_{icd} = \alpha &+ \beta^{RW}(RW_i)\tau_c + \gamma^{RW}(RW_i)\tau_c\nu_{c,\ 2016}^{\text{Rep., Pres.}} + \beta^{DW}(DW_i)\tau_c + \gamma^{DW}(DW_i)\tau_c\nu_{c,\ 2016}^{\text{Rep., Pres.}}\\ &+ \beta^{RM}(RM_i)\tau_c + \gamma^{RM}(RM_i)\tau_c\nu_{c,\ 2016}^{\text{Rep., Pres.}} + \beta^{DM}(DM_i)\tau_c + \gamma^{DM}(DM_i)\tau_c\nu_{c,\ 2016}^{\text{Rep., Pres.}}\\ &+ \text{Candidate}_i + \boldsymbol{\Delta}_1\boldsymbol{\nu}_{c,2016}^{\text{Rep., House}} + \boldsymbol{\Delta}_2\boldsymbol{\nu}_{c,2012}^{\text{Rep., Pres.}} + \boldsymbol{\Gamma}\boldsymbol{X}_{ic} + \varepsilon_{icd},\end{aligned}$$

where the main coefficients of interest are the γ^j's. For example, $\gamma^{DW} > 0$ implies a positive effect of the MeToo movement on Democratic women candidates in counties with high existing Republican support. Similarly, $\gamma^{RM} < 0$ implies that Republican men candidates do worse in these same counties. The Republican presidential vote share in specification (4) is centered at 50%, so that the DD estimates β's can be easily interpreted as the effect of the MeToo tweets on candidate vote share when the 2016 presidential Republican vote share is split right down the middle.

Columns (3)–(5) of Table III confirms the above hypotheses. In column (3), the anticipated advantage for Democratic women and Republican men candidates are present in counties with high existing Republican support. The estimated coefficients of β^{DW} and γ^{DW} suggest that for counties with high MeToo tweets, Democratic women face a disadvantage when there is a 50-50 split, and this effect reverses in counties with high Republican support. The estimate of γ^{RM} is negative, implying that the Republican men face a disadvantage in the same counties where the Democratic women get an advantage. Column (4) uses only the two-party vote shares on both sides of the equation, and the results are similar.

[30] Binned scatter plots are with past electoral trends already partialed out.

The estimate of γ^{DW} from column (4) implies that in counties with a standard deviation increase in the presidential Republican vote share above the 50-50 split (67.5% Republican vote share), a standard deviation increase in the county log MeToo tweet density (1.164) gives Democratic women candidates a 0.96 percentage point vote share advantage ($\rho < 0.01$) relative to their peers in counties with a 50–50 split in the Republican vote share.[31] Republican men on the other hand, incur a 0.45 percentage point disadvantage ($\rho < 0.05$).[32] The estimate of γ^{DM} is only marginally significant, suggesting that the advantage of Democrats came mainly through their women candidates. To further place the estimates in perspective, counties with a 50-50 split or with lower than 50% existing support for the Republican party are a minority in the two-party sample (approximately 22%). The estimates β^{DW} and γ^{DW} suggest that an absolute advantage begins after the 69% Republican vote share mark (approximately 46% of the two-party observations).[33]

Column (5) uses district fixed effects instead of candidate fixed effects, and the results barely change, indicating that both observed and unobserved characteristics of the candidates, including experience, grassroots campaigning and support, and funding, are unlikely to be driving the results.[34]

4.4 Robustness

Table IV examines robustness of the results in column (4) of Table III. The estimated joint effect of the MeToo movement and the Republican vote share for the Democratic women and Republican men is consistent throughout, while the effect for the Democratic men is not. In column (1), the tweets measure is computed using only tweets that occur before June, the earliest month in which a substantial number of states (17) have their primary elections. This mitigates the astroturfing concern (which I discuss below in Section 5.1).

Column (2) excludes districts with only one or two counties. This ensures that

[31] Or, $0.047 \times (67.5 - 50) \times 1.164$.

[32] Or, $-0.023 \times (67.5 - 50) \times 1.164$

[33] I do not fully understand this pattern. One explanation might be a systematic difference between the kind of MeToo tweets which appears in Democratic vs. Republican counties, where those appearing in Democratic counties are tweets opposing the MeToo movement, while the MeToo tweets in Republican counties are genuinely representing the spirit of the MeToo movement and having an anti-Republican sentiment. Another explanation might be that the MeToo tweets capture mostly capture the expected pro-women and anti-Republican sentiment in a county, but the tweets mobilised Republican voters in retaliation in the Democratic counties with a woman candidate.

[34] Districts with a low margin of victory (< 5%) in the 2018 House elections have a more pronounced effect (Table A9).

the DD specification picks up the intended within-district effect of the tweets, and are not driven by districts with a small number of counties. In columns (3) and (4), counties with low turnout ($< 2{,}000$) and counties with low voting-aged population ($< 2{,}000$) are dropped to mitigate concerns that the MeToo effect is present only in small areas.

In column (5), districts with low geographical variation in the tweets measure (low standard deviation across counties of a district) are dropped to mitigate another astroturfing concern (Section 5.1). In column (6), counties on extreme tails of high-speed internet connectivity are excluded so that the results are representative of the average geographical area by internet use.[35]

Finally, column (7) exclude districts where incumbents have vacated their seats. In the 2018 House elections, 36 Republicans and 18 Democrats did not seek re-election. In the two-party sample, open seats account for approximately 15% of the observations. Excluding these district observations with open seats do not change the results.[36]

5 Additional Results and Interpretations

5.1 What do the MeToo Tweets Measure?

Astroturfing. A basic sanity check concerns an implicit assumption in this paper. Are the tweets a proxy of the grassroots movement or are they from astroturfing? While definitive evidence is difficult, arguments can be made against it.

First, the correlation between the MeToo tweet measures and county demographics provide evidence against astroturfing. The tweets measure is highly correlated with percentage females, Hispanic, foreign-born, aged 29 and under, and college education or higher, in the expected positive direction, while being negatively correlated with the percentage of residents living in rural areas (Figure A5).

[35] Outliers in high-speed broadband connection might include those municipals where internet access is either partially or fully provided by the local governments, and these areas are arguably more left-leaning with the public provision of what is otherwise a private good. Omitting these places suggest that the results are not simply driven by these pro-Democratic areas.

[36] In Table A4 of the appendix, I also check that the results hold with non-nested two-way clustering of the house candidates and counties; with a general specification of the log tweet density measure where the coefficients of log tweets and log population are allowed to differ; with the incontiguous Hawaii state observations dropped from the sample, and with the tweets measure computed using only the tweets without other hashtags present to prevent it from picking up other grassroots sentiments and tweets with overt political angles (e.g. "#bluewave").

This does not square with a broad-based generation of fake grassroots.

Second, as indicated in Figure I, both the global MeToo tweets and those that are successfully matched to U.S. counties have spikes in intensity that coincide with high-profile MeToo events. This supports the assumption that the tweets are capturing grassroots sentiments.[37]

A check against astroturfing is to cut off aggregation of the 2018 tweets measure before June when most primary elections occur.[38] Astroturfing might begin early in the year, but candidates are not yet finalised and funds, if any, diverted to astroturfing will likely yield higher benefits much closer to the elections in November. Another potential sign of astroturfing is when the MeToo tweets are highly uniform in a district. Table IV shows that the conclusion is unaffected when using only pre-primary (pre-June) tweets and when dropping districts with low within-district variation in the tweets measure.

Sexual harassment and disapproval of the Republican party (VOTER survey). Another check that MeToo tweets measure pro-women and anti-Republican sentiment comes from the 2018 *VOTER* (Views of the Electorate Research) survey (Democracy Fund Voter Study Group 2018), which tracks about 8,000 individuals from 2012–18, though some individuals drop out of the study from 2016–18. I use the reported ZIP code and match them to (primary) counties using the FIPS from the U.S. Cities Database. Out of the 2,649 counties in the sample, 1,352 counties can be successfully matched to the VOTER microdata. 7,491 individuals are ultimately matched to the county-level tweet density data.[39]

Table V presents the results using the microlevel VOTER data on attitudes towards sexual harassment. All regressions control for individual characteristics, their political interest and knowledge, and their voting history.[40] Overall, the tweets capture individual pro-feminist (anti-sexism) and anti-Republican attitudes. First, I regress an aggregated "sexism" score based on six questions that proxy for attitudes toward gender roles and sexual harassment, which is increasing in sex-

[37] See note 10

[38] 17 states have their primaries in June. See `http://www.ncsl.org/research/elections-and-campaigns/2018-state-primary-election-dates.aspx`.

[39] Change variables are computed for individuals that have been tracked throughout.

[40] The set of individual characteristics include gender, race, education, employment, birth cohort (by decade), income, marital status, and number of children. The set of controls for voting history and tendency include whom the respondent would have voted for in a presidential election and for congress when asked in 2012 ((1) Democratic, (2) Republican, (3) Other/not sure/would not vote), plus the two indicators who whether the respondent always vote the same party. 1,809 respondents (23.4%) indicate that they always vote Republican, 2,287 (29.6%) indicate that they always vote Democratic, and the remaining 3641 (47.1%) indicate they vote for both. The regressions also control for interest and knowledge in current affairs and politics on a four-point scale.

ism.[41] The tweets measure is negatively correlated with the sexism measure in both the 2016 and 2018 waves in columns (1)–(2), as anticipated. The tweets measure however, does not predict any change in sexism (column (3)). Column (4) indicates the tweets measure is not just picking up concerns about broader "problems in society".

In column (5), the tweets measure implies that respondents from counties with higher MeToo tweet incidences are less approving of the Republican party. The tweets measure however, does not predict approval of the Democratic party in column (6). As expected, whether an individual always votes Democratic or Republican is also highly correlated with the party's approval. Overall, the results from Table V indicate that the county-level MeToo tweets in 2018 are indeed correlated with attitudes of the electorate towards harassment and the political parties' handling of it.[42]

5.2 Turnout as a Channel

The 2018 midterm elections set a record high in turnout.[43] A natural question is whether the MeToo movement had a part to play in increasing turnout. To test this, I estimate the model:

$$t_c^{\text{House 2018}} - t_c^{\text{House 2016}} = \alpha + \beta_1 \tau_c + \beta_2 \nu_{c,\ 2016}^{\text{Rep., Pres.}} + \gamma(\tau \cdot \nu^{\text{Rep., Pres.}})_c + \mathbf{\Gamma} \boldsymbol{X}_c + \varepsilon_c, \tag{5}$$

where t_c is log total votes cast in the House elections in county c, so that the dependent variable is the log change in total votes cast from 2016 to 2018, which is interpreted as a percentage change. The baseline controls include the county demographics and past electoral turnout.

Table VI presents the results, which is consistent with the heterogeneous effect in Table III. First, columns (1)–(2) show that the log tweet density measure does not predict any change in turnout. In columns (3)–(4), I replace the tweets measure with the log tweet *intensity* measure (without dividing by county population), and

[41] For example, one question gets respondents to respond to the statement "*Women who complain about harassment often cause more problems than they solve*". Responses go from a scale of 1–4 (strongly agree to strongly disagree).

[42] Table A6 of the appendix uses the VOTER microdata with further evidence that the tweets capture an anti-Republican sentiment. The results imply that the log tweet density measure of an individual's county is negatively and statistically associated with the probability of voting Republican in the presidential and congressional elections, conditional on the same controls in Table V. Further, the tweet density measure also increases the probability that the individual switch their vote to the Democratic party from 2016 to 2018.

[43] washingtonpost.com/news/monkey-cage/wp/2018/11/20/americans-just-set-a-turnout-record-for-the-midterms-voting-at-the-highest-rate-since-1914-this-explains-why/.

the interaction term (γ in equation (5)) is now positive. The estimate in column (4) implies that for a standard deviation increase in log tweets intensity (1.946), every 10 percentage point increase in the Republican vote share increases turnout by 1.17% ($\rho < 0.05$).

The results in Table VI lack a causal interpretation since the tweets measure may be picking up on existing upward trends in political engagement and turnout. To test this, I repeat the regressions in Table VI, but with the increase in 2012–16 presidential turnouts as the dependent variable, and the results confirm that no such trend exists before 2016 (Table A5). Figure VII show that the MeToo movement on Twitter begins in full force only from 16 Oct 2017.[44]

The results from Table VI suggest that the intensity of the MeToo movement is what matters for turnout. The finding on turnout connects with a set of existing literature. For example, DellaVigna and Kaplan (2007) find that the Republican-leaning Fox News increased turnout (and also the Republican vote share) in the 2000 presidential elections. Campante et al. (2017) in particular, provides some insight into the MeToo movement as a grassroots protest. In the context of Italy, they find that the internet facilitated local online grassroots protest movements, and that the new Italian political party in 2009 (M5S) grew out of those online protest groups and is overrepresented by supporters who did not vote in the previous elections.

5.3 County-level Vote Changes

If turnout is a channel, then the anti-incumbency effect of the MeToo movement should also be observed through changes in the district-county level vote shares. To test this, I regress the district-county level change in the Republican House vote share from 2016 to 2018.

Table VII documents the results, which suggest that in places with a Republican stronghold, there is a fall in the house Republican vote share from 2016 to 2018. In columns (1) and (3), the estimates imply that for a standard deviation increase in the log tweet density measure (1.17) and the Republican vote share (17.7), the all-party Republican vote share drops by 0.59 percentage points ($\rho < 0.01$), and for the two-party vote share, it is a 0.28 percentage point drop ($\rho < 0.05$). The drop in the Republican two-party vote share is about half the magnitude of the all-party

[44] The equivalent is to test 2014–16 House turnout, but county-level House returns are available only from 2016 onwards.

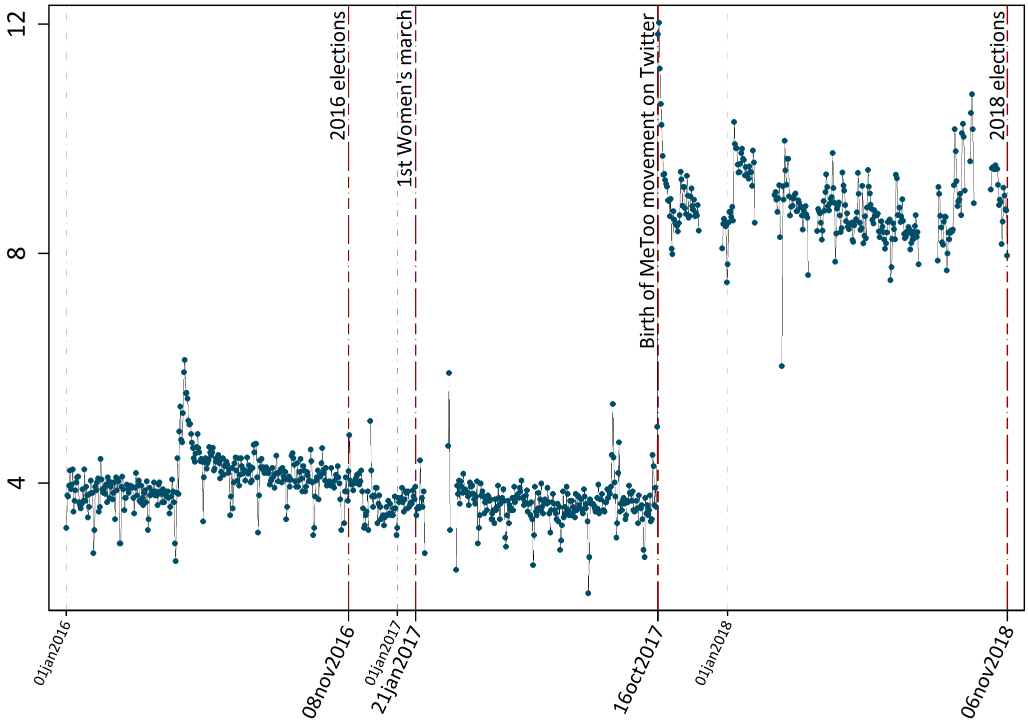

Figure VII: Extended Timeline of MeToo Tweets[46]

vote share, consistent with a shift of votes mostly from the independent (rather than Republican) to Democratic.[45]

Columns (2) and (4) include the change in log turnout between 2016 and 2018 and the estimates, while only marginally significant, have a negative sign which is consistent turnout as a channel of the MeToo effect. The estimate from column (4) implies that a standard deviation percentage increase in turnout (0.44) decreases the Republican two-party vote share by 1.4 percentage points ($\rho < 0.1$).

As another placebo test, column (5) checks that the estimates are not capturing existing downward trends in Republican support by geography—that counties with a high Republican vote share in 2016 are not those with a drop in the 2012–16 Republican presidential vote share. Column (6) checks that the estimates are not capturing existing downward trends by anti-Republican sentiment—that counties with a high Republican vote share in 2012 are those with a drop in the 2012–16 presidential Republican vote share.[47]

[45] In Table A8 of the appendix, I repeat the regressions using log tweets as an intensity measure instead of the log tweets density measure (normalised by county population), and the results are more significant overall, both in terms of economic and statistical significance.

[46] The MeToo movement blew up on Twitter on October 16, 2017 when Alyssa Milano started using the MeToo hashtag to encourage people to share their stories. This day is the peak of the movement so far, as indicated by the peak in the figure. Figure A2 plots the timeline in level terms.

[47] Placebo results have the same conclusion with the all-party presidential Republican vote share.

5.4 Interpreting the Results

The main finding is that the tweets capture an advantage for Democratic women, and a disadvantage for the Republican men, but only in counties that are Republican (high 2016 presidential Republican vote share). There are several interpretations of the results. One is a selection of women candidates into areas with a high incidence of the MeToo movement. Section 3.2 tests and rejects this selection issue.

A second interpretation is that the MeToo tweets, and by extension the movement, is a signal of the intent to turn out to vote for the Democratic women and against the Republican men. Table V supports this interpretation, where the tweets capture pre-existing but not changes in individual attitudes on sexism.[48] This however, does not rule out a mobilising effect of the movement through social media.

A third interpretation is that the MeToo movement mobilised voters to turn out and vote for the women candidates who are mostly Democratic and therefore benefited the Democratic party. The results from Table VI supports this, with the tweets capturing an increase in the House turnout, but only in the Republican strongholds. In addition, the tweets capture a decrease in the house Republican vote share between 2016 and 2018. Neither of these results can be replicated using data for the 2016 Presidential elections, supporting the idea that the MeToo effect did not exist before 2016.

The specification in equation (4) also directly supports the interpretation that the MeToo movement was at least partially motivated against the Republican presidential candidate Donald Trump. Two Women's marches are closely tied to the movement. The first occurred on 21 January 2017, protesting Donald Trump's first day in office. An estimated 3–5 million people took part in the marches, which arguably qualifies as the largest protest in U.S. history.[49] The second march happens exactly a year later in 2018, still, protesting the Trump presidency and encouraging voters to turn out to vote.[50]

These results fit in with the literature on electoral turnout and returns. While the effect of internet diffusion is to decrease turnout (e.g. Falck et al. 2014; Gavazza et al. 2018; Miner 2015, these are usually interpreted as substitution away from politically rich media content to entertainment made available from high-speed connection (e.g. media streaming and online gaming). Moreover, the effect of an

[48] The 2016 survey responses are from December, after the 2016 elections).

[49] https://www.washingtonpost.com/news/monkey-cage/wp/2017/02/07/this-is-what-we-learned-by-counting-the-womens-marches/.

[50] https://www.nytimes.com/2018/01/20/us/womens-march.html.

independent media, if any, tends to be anti-incumbent (e.g. Campante et al. 2017; Enikolopov et al. 2011; Miner 2015).

On a final note, the intensive margin of the online MeToo movement seems to be the driving factor. I first decompose the tweet density measure into the number of MeToo tweets per author (intensive margin) and number of authors per population (extensive margin).[51] Table VIII documents the results, and the log MeToo tweets per author is the measure that replicates the baseline finding—Republican counties where the MeToo tweet authors post more MeToo tweets are counties with a greater backlash against Republican men.

6 Conclusion

In this paper, I investigate the connection between the MeToo movement and the 2018 midterm House elections. The MeToo effect is observed only in Republican counties, where the Democratic women face an advantage and the Republican men a disadvantage. The evidence also suggests that turnout is a key channel.

The results are consistent with the assertions that MeToo movement became a left-leaning political movement that mobilises voters to turn out to vote Democratic and for women candidates (who are mostly Democratic), and that this effect is present only in the Republican strongholds. Results from the VOTER survey microdata confirms that the MeToo tweets measure what they are supposed to measure in the context of this study—a pro-women thermometer and a general anti-Republican sentiment.

This study adds to the literature on the political economy of the mass media and its effect on electoral outcomes. The focus is on the House elections instead of the Senate because only a third of Senate seats are up for election. The House is an important part of the national legislation and, keeping with the theme of the grassroots, is the legislation that is more responsive to what their constituencies need. Furthermore, the House has the power to initiate impeachment, as is the case with the Republican president at the time of this writing.[52]

Potential avenues of research include whether the MeToo effect persists into the next round of elections, which include the Republican president, a subject of

[51] Or, $ln\left(\frac{\text{\#MeToo tweets}}{\text{county population}}\right) = ln\left(\frac{\text{\#MeToo tweets}}{\text{\#authors}}\right) + ln\left(\frac{\text{\#authors}}{\text{county population}}\right)$. Where #authors is the unique number of twitter users contributing to the 2018 MeToo tweets in the sample.

[52] On allegations that President Trump leveraged his position in the White House to pressure foreign leaders into investigating his political opponents in the coming elections.

the movement himself. Given how state judges were recalled for being lenient in sexual assault cases, another potential study relating legal realism is on whether the movement induces harsher sentencing in sexual assault crimes.[53]

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[53] At the time of writing, Twitter CEO Jack Dorsey announced a ban on all paid political advertising, stating that political messages "should be earned, not bought" (Rajan 2019). While Facebook is the dominant platform for political advertising, Twitter's policy acknowledges the potential influence of political campaigns on social media.

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7 Tables

Table I
SUMMARY STATISTICS

	Mean	Std. Dev.	Min	Max	Obs.
Log no. of MeToo tweets	2.396	(2.361)	0.000	10.601	8654
Candidate characteristics					
Challenger (%)	68.847	(46.315)	0.000	100.000	8654
Woman (%)	20.857	(40.631)	0.000	100.000	8654
Black (%)	0.404	(6.347)	0.000	100.000	8654
Hispanic (%)	3.547	(18.499)	0.000	100.000	8654
White (%)	94.754	(22.297)	0.000	100.000	8654
District Seat characteristics					
Republican incumbent (%)	65.091	(47.671)	0.000	100.000	8654
Democratic incumbent (%)	17.056	(37.614)	0.000	100.000	8654
Open seat (%)	17.587	(38.073)	0.000	100.000	8654
No main challenger (%)	1.502	(12.165)	0.000	100.000	8654
Electoral variables					
2016 House Rep. vote share (%)	63.859	(21.597)	0.000	100.000	8482
2016 House turnout ('000)	96.860	(282.419)	0.000	3129.539	8654
2012 Pres. Rep. vote share (%)	57.538	(15.554)	5.978	95.862	8646
2012 Pres. turnout ('000)	96.032	(281.350)	0.000	3181.067	8654
2016 Pres. Rep. vote share (%)	60.323	(16.936)	8.296	96.033	8646
2016 Pres. turnout ('000)	102.954	(304.243)	0.000	3434.308	8654
Census variables 2012–16 ACS average					
Population ('000)	259.121	(851.295)	0.076	10′057.155	8642
Black (%)	8.737	(13.066)	0.000	81.533	8642
Hispanic (%)	10.804	(14.750)	0.000	98.959	8642
White (%)	74.841	(20.668)	0.760	100.000	8642
Foreign born (%)	6.110	(7.443)	0.000	52.230	8642
Female (%)	50.060	(2.163)	21.513	56.418	8642
Age 29 and under (%)	37.575	(5.399)	11.842	70.981	8642
Age 65 and over (%)	17.150	(4.576)	3.855	53.106	8642
Median HH income ('000)	50.089	(13.765)	18.972	125.672	8642
Unemployment (%)	7.077	(3.000)	0.000	29.927	8642
HS or less (%)	13.928	(6.317)	1.279	51.479	8642
College or more (%)	22.512	(10.198)	2.985	80.210	8642
Rural population (%)	51.696	(33.614)	0.000	100.000	8646

Notes—Observations are at the county level. Ethnic of house candidates are inferred using the Name Prism API (Ye et al., 2017). Republican vote share is computed as total number of vote cast for the Republican party divided by the total number of votes cast. House vote shares reported in this Table is the all-party vote share. Presidential vote shares are always two-party vote shares. County census variables come from the ACS (American Community Survey) 5–year estimates for 2012–16. Observations unweighted.

Table II
SELECTION OF TWEET DENSITY IN COUNTIES

	ln (tweets density) in 2018 with meToo hashtag				
	(1)	(2)	(3)	(4)	(5)
House Rep. vote share in 2016		0.009***	0.007***	0.003	0.003
		(0.002)	(0.002)	(0.004)	(0.004)
House elections turnout in 2016		0.017**	0.007	−0.005	−0.004
		(0.007)	(0.005)	(0.008)	(0.008)
Pres. Rep. vote share in 2016		−0.020***	−0.009**	−0.005	−0.007
		(0.004)	(0.004)	(0.005)	(0.005)
Pres. Rep. vote share change (2012–16)		−0.018***	0.011**	0.014	0.006
		(0.006)	(0.006)	(0.012)	(0.012)
Pres. election turnout in 2016		0.002	0.001	0.023**	0.021**
		(0.010)	(0.006)	(0.010)	(0.010)
Pres. election turnout change (2012–16)		0.005	0.003	−0.014	−0.015
		(0.010)	(0.007)	(0.010)	(0.010)
%Female × (High-speed connection)	0.105***	0.030	−0.044	−0.002	−0.004
	(0.036)	(0.032)	(0.032)	(0.033)	(0.033)
Constant	−7.416***	−8.131***	−8.444***	−7.824***	−7.685***
	(1.219)	(1.151)	(1.286)	(1.488)	(1.488)
Control variables					
2016 House elections		X	X	X	X
2012–16 Presidential election		X	X	X	X
Census Control			X	X	X
U.S. House District F.E.				X	X
F-test: County census controls = 0			$F = 23.55$***	$F = 14.33$***	$F = 14.82$***
R^2	0.066	0.128	0.273	0.384	0.384
N	2466	2427	2427	2427	2427

Notes—Observations are at the county level. The dependent variable is tweet density—the (natural) log of the ratio of the number of tweets in 2018 which contains the MeToo hashtag, to population size. High-speed connection is the ratio of residential households in a county with high-speed internet connections from the FCC. Republican vote share is the votes received by the Republican candidate (party) in the Presidential (House) election, divided by the total number of votes cast. Turnout is the number of votes cast divided by the number of voting-aged population. County census controls for demographics come from the ACS (American Community Survey) 5-year estimates for 2012–16—they include 14 demographic variables of ethnic, gender, age, education, and foreign-born composition, income and employment rate, and rural-urban composition data. Column (5) uses the two-party Republican vote share—number of votes received by the Republican candidate divided by votes received by both the Republican and Democratic candidates. Robust standard errors in parentheses clustered at the 388 U.S. House congressional districts.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table III

The Effect of the MeToo Movement on Candidate Vote Share

			Heterogeneous effect, by presidential Republican vote share in 2016		
	All-party vote share			Two-party vote share	
	(1)	(2)	(3)	(4)	(5)
Rep. woman × (Log tweet density)	−3.557***	−0.674	−0.707	−0.472	−0.193
	(0.993)	(0.574)	(0.724)	(0.713)	(0.699)
Dem. woman × (Log tweet density)	2.073***	0.074	−0.655***	−0.930***	−0.636**
	(0.492)	(0.188)	(0.253)	(0.287)	(0.312)
Rep. man × (Log tweet density)	−2.218***	0.008	0.300	0.408	0.302
	(0.410)	(0.157)	(0.235)	(0.255)	(0.272)
Dem. man × (Log tweet density)	2.316***	0.279	−0.029	−0.439	−0.592
	(0.515)	(0.232)	(0.354)	(0.431)	(0.436)
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)			−0.023	−0.027	−0.027
			(0.030)	(0.029)	(0.028)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)			0.037***	0.047***	0.043***
			(0.014)	(0.013)	(0.015)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)			−0.021**	−0.022**	−0.024**
			(0.009)	(0.009)	(0.010)
Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)			0.014	0.027*	0.035**
			(0.014)	(0.015)	(0.015)
Control variables					
Candidate fixed effects	*X*	*X*	*X*	*X*	
District fixed effects					*X*
2016 House & 2012–16 Pres. election		*X*	*X*	*X*	*X*
County census demographics		*X*	*X*	*X*	*X*
Racial & gender voting		*X*	*X*	*X*	*X*
F-test: House & 2012–16 Pres. election = 0		$F = 297.71$***	$F = 13.07$***	$F = 15.63$***	$F = 12.17$***
F-test: Census controls = 0		$F = 3.82$***	$F = 3.55$***	$F = 4.14$***	$F = 2.63$***
F-test: Racial & gender voting = 0		$F = 3.81$***	$F = 4.53$***	$F = 9.16$***	$F = 2.94$***
Main-party candidates only				*X*	*X*
R^2	0.907	0.975	0.977	0.952	0.886
N	8634	8470	8470	6234	6234

Notes—The dependent variable is the candidate vote share at the district-county level. Tweet density is the (natural) log of MeToo tweets in 2018 divided by county population. Past electoral controls include: (1) 2016 house Republican vote share, (2) 2016 presidential Republican vote share, and (3) 2012–16 presidential Republican vote share change, fully interacted with party. County census controls for demographics come from the ACS 5-year estimates for 2012–16—they include 14 demographic variables of ethnic, gender, age, education, and foreign-born composition, income and employment rate, and rural-urban composition data. Controls for voting by racial and gender lines include interacting politician gender and ethnic (White, Black, Hispanic, and Others) with the corresponding county ethnic percentage. Ethnic of a politician is inferred using their names through the NamePrism API (Ye et al., 2017). Columns (4)–(5) includes only main-party candidates and uses two-party vote shares on both sides of the equation. Robust standard errors in parentheses are clustered by candidates.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table IV
Robustness

	Robustness check for Column (4) of Table III						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.039	−0.039	−0.028	−0.028	−0.027	−0.029	−0.012
	(0.032)	(0.036)	(0.030)	(0.030)	(0.029)	(0.038)	(0.025)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.047***	0.049***	0.051***	0.051***	0.047***	0.043***	0.044***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.021**	−0.025***	−0.028***	−0.025***	−0.022**	−0.030**	−0.024***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)
Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.022*	0.039***	0.033**	0.028*	0.027*	0.014	0.032**
	(0.013)	(0.013)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)
Control variables							
Candidate fixed effects	*X*	*X*	*X*	*X*	*X*	*X*	*X*
2016 House & 2012–16 Pres. election	*X*	*X*	*X*	*X*	*X*	*X*	*X*
County census demographics	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Racial & gender voting	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Pre-primary MeToo tweets	*X*						
Counties > 2		*X*					
Turnout > 2000			*X*				
Voting population > 2000				*X*			
District std. dev. tweets > 5th percentile					*X*		
High-speed internet bw. 5th & 95th percentile						*X*	
Non-vacated seats							*X*
R^2	0.952	0.953	0.946	0.949	0.950	0.957	0.953
N	6234	5872	5821	5983	6065	5289	5311

Notes—This Table presents a set of robustness checks for column (4) of Table III. In column (1), the tweets measure is cut off before June, when most (17 states) of the primary elections took place. In the column (2) sample "Counties > 2", districts with 1 or 2 counties are dropped. In column (3), the sample "Turnout > 2000" excludes counties with fewer than 2,000 votes cast in the 2018 House elections. In column (4), the sample "Voting population > 2000" excludes counties with an estimated ACS voting-aged population of fewer than 2,000. In column (5), the sample "Std. dev. tweets > 5th percentile" excludes districts where the geographical variation in the MeToo tweets is below the 5th percentile. In column (6), the sample "High-speed internet bw. 5th & 95th percentile" includes only counties where the high-speed internet measure from the FCC is between the 5th & 95th percentile. In column (7), the sample "Non-vacated seat" drops open-seat districts where the incumbent has retired. All controls are otherwise the same. Robust standard errors in parentheses are clustered by candidates.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table V

Correlation between the MeToo Movement and Individual Attitudes (VOTER Data)

	Sexism 2016 (Range 1 to 24)	Sexism 2018 (Range 1 to 24)	Change in sexism (Range -23 to 23)	𝟙(Allegations indicative of wider problems)	Approval of Rep. party in handling harassment (Range 1 to 4)	Approval of Dem. party in handling harassment (Range 1 to 4)
	(1)	(2)	(3)	(4)	(5)	(6)
Log of tweet density	-0.096^{***}	-0.134^{***}	0.009	0.011^{*}	-0.035^{***}	0.013
	(0.036)	(0.050)	(0.034)	(0.006)	(0.012)	(0.013)
𝟙(Always vote for Democrats)	-0.289^{***}	-0.204	0.016	0.035^{*}	-0.103^{***}	0.116^{***}
	(0.112)	(0.138)	(0.113)	(0.018)	(0.036)	(0.035)
𝟙(Always vote for Republicans)	0.823^{***}	1.032^{***}	0.057	-0.015	0.242^{***}	-0.107^{***}
	(0.117)	(0.171)	(0.128)	(0.025)	(0.040)	(0.040)
Control variables						
Individual characteristics	X	X	X	X	X	X
Voting history & tendency	X	X	X	X	X	X
Political interest & knowledge	X	X	X	X	X	X
F-test: Individual characteristics = 0	$F = 12.78^{***}$	$F = 9.34^{***}$	$F = 1.27$	$F = 3.84^{***}$	$F = 1.33^{*}$	$F = 3.02^{***}$
F-test: Voting tendency = 0	$F = 546.05^{***}$	$F = 242.62^{***}$	$F = .66$	$F = 101.44^{***}$	$F = 315.92^{***}$	$F = 216.49^{***}$
F-test: Political interest & knowledge = 0	$F = 4.45^{***}$	$F = .63$	$F = 1.06$	$F = .11$	$F = 3.03^{**}$	$F = 1.32$
R^2	0.393	0.393	0.015	0.187	0.351	0.307
N	6625	3908	3816	3972	3931	3934

Notes—Observations are individual respondents in the Democracy Fund VOTER (Views of the Electorate Research) survey. All regressions control for individual characteristics including gender, race, education, employment, birth cohort (by decade), income, marital status, and number of children. Voting history & tendency controls include which party the individual would have for congress and president in 2012, and an indicator for whether the individual always for for the same party. Political interest and knowledge controls for the level of interest and knowledge the individual has in politics and current affairs. The dependent variable in columns (1)–(2) is an aggregated score from *sexism1–sexism6* in the VOTER survey, which is increasing in "sexism". The dependent variable in column (3) is the change in this score for the same individual from 2016–18. The dependent variable in column (4) is a dummy for whether the respondent thinks that recent allegations of sexual harassment and assault reflect widespread problems in society. The dependent variable in column (5) and (6) is the approval rating of the Republican and Democratic party in the handling of harassment and assault in politics. Robust standard errors clustered by counties reported in parentheses.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table VI
The Effect of the MeToo Movement on Turnout

	Measure of county-level MeToo movement (τ) is			
	ln(No. of tweets divided by population)		ln(No. of tweets)	
	(1)	(2)	(3)	(4)
τ	0.0136	-0.0213	0.0094	-0.0321
	(0.0125)	(0.0458)	(0.0117)	(0.0240)
Pres. 2016 Rep. vote share	-0.0113^{***}	-0.0072	-0.0112^{***}	-0.0122^{***}
	(0.0039)	(0.0069)	(0.0039)	(0.0038)
$\tau \times$ (Pres. 2016 Rep. vote share)		0.0005		0.0006^{**}
		(0.0006)		(0.0003)
District fixed effects	X	X	X	X
Census Control	X	X	X	X
F-test: Electoral controls = 0	$F = 14.89^{***}$	$F = 6.11^{***}$	$F = 14.74^{***}$	$F = 12.48^{***}$
F-test: County census = 0	$F = 3.04^{***}$	$F = 2.91^{***}$	$F = 2.48^{***}$	$F = 2.17^{**}$
R^2	0.6790	0.6793	0.6787	0.6796
N	2593	2593	2593	2593

Notes—Observations are at the county level. The dependent variable is the log of total county votes cast in the 2018 House elections minus the same variable for the 2016 House elections. In columns (1)–(2), the measure of the MeToo movement is the log of county-level MeToo tweets divided by county population; in columns (3)–(4) the measure is the log of county-level MeToo tweets. Pres. 2016 Rep. vote share is the two-party county-level vote share of the Republican candidate in the 2016 presidential election. County census controls for demographics from the ACS 5-year estimates for 2012–16 also includes voting-aged population in this Table. Controls also include the turnout for both the 2016 Presidential and House elections, and the 2012 presidential Republican vote share. Robust standard errors in parentheses are clustered by districts.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table VII

Change in Republican Vote Share, District-County Level

	Change in *house* Republican vote share between 2016 and 2018				Placebo specifications	
	Change in all-party vote share		Change in two-party vote share		Change in *presidential* Republican vote share between 2012 and 2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Log tweet density × (Pres. 2016 Rep. vote share)	−0.0284***	−0.0271***	−0.0137**	−0.0124*	−0.0027	
	(0.0084)	(0.0083)	(0.0069)	(0.0068)	(0.0026)	
Log tweet density × (Pres. 2012 Rep. vote share)						0.0030
						(0.0028)
Log tweet density	0.3789	0.4202**	0.0736	0.1115	0.0077	−0.2328
	(0.2369)	(0.1988)	(0.2607)	(0.2174)	(0.0560)	(0.1687)
Change in log(total House votes) 2016–18		−3.0047*		−3.0129*	−0.0163	−0.7165**
		(1.6895)		(1.7049)	(0.1006)	(0.3091)
Change in log(total Pres. votes) 2012–16					−3.3858*	−2.1329
					(1.9358)	(1.6345)
Control variables						
District fixed effects	X	X	X	X	X	X
Past electoral controls	X	X	X	X	X	X
County census demographics	X	X	X	X	X	X
R^2	0.8889	0.8937	0.9049	0.9096	0.8728	0.9080
N	3102	3102	3102	3102	3102	3102

Notes—Observations are at the district-county level. The dependent variable is the change in Republican vote share. In columns (1)–(2), it is the all-party change in Republican vote share in the House elections from 2016–18. In columns (3)–(4) the dependent variable is the same variable for the two-party vote share. In columns (5)–(6), the dependent variable is the change in the presidential Republican (two-party) vote share from 2012–16. The electoral control variables in columns (1)–(4) include the house Republican vote share in 2016, and the change in presidential Republican vote share from 2012–16; in columns (5)–(6) the electoral controls are the house Republican vote share in 2016, and the change in presidential Republican vote share from 2008–12. All specifications otherwise include district fixed effects and the county demographics. Robust standard errors in parentheses are clustered by the 388 U.S. House congressional districts.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table VIII
The Intensive and Extensive Margins of MeToo Movement

	This Table breaks down the tweet density into MeToo tweets per MeToo author and MeToo authors per population		
	All-party	Two-party	
	(1)	(2)	(3)
Log MeToo tweets per author			
Rep. woman × (Log tweets per author) × (Pres. 2016 Rep. vote share)	−0.142*	−0.092	−0.135*
	(0.081)	(0.077)	(0.079)
Dem. woman × (Log tweets per author) × (Pres. 2016 Rep. vote share)	0.134***	0.102**	0.050
	(0.048)	(0.040)	(0.042)
Rep. man × (Log tweets per author) × (Pres. 2016 Rep. vote share)	−0.119***	−0.076***	−0.035
	(0.028)	(0.025)	(0.026)
Dem. man × (Log tweets per author) × (Pres. 2016 Rep. vote share)	0.100***	0.064**	0.037
	(0.032)	(0.032)	(0.033)
Log author density			
Rep. woman × (Log author density) × (Pres. 2016 Rep. vote share)	0.018	−0.006	0.010
	(0.031)	(0.024)	(0.027)
Dem. woman × (Log author density) × (Pres. 2016 Rep. vote share)	0.009	0.031**	0.040**
	(0.016)	(0.015)	(0.018)
Rep. man × (Log author density) × (Pres. 2016 Rep. vote share)	0.003	−0.006	−0.021
	(0.011)	(0.011)	(0.014)
Dem. man × (Log author density) × (Pres. 2016 Rep. vote share)	−0.004	0.016	0.034*
	(0.018)	(0.019)	(0.020)
Control variables			
Candidate fixed effects	*X*	*X*	
District fixed effects			*X*
2016 House & 2012–16 Pres. election	*X*	*X*	*X*
County census demographics	*X*	*X*	*X*
Racial & gender voting	*X*	*X*	*X*
Main-party candidates only		*X*	*X*
R^2	0.975	0.952	0.886
N	8634	6234	6234

Notes—This Table replicates columns (3)–5) of Table III, except that in this Table the log tweet density measure is decomposed into a log MeToo tweets per MeToo author and a log MeToo author density (log MeToo author at the county level divided by county population). All other controls are the same. Robust standard errors in parentheses are clustered by candidates.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

A Appendix

A.1 Data Details

To download and map the tweets to counties, I proceed as follows:

1. I use the *GetOldTweets-python* pseudo-API by Jefferson Henrique (https://github.com/Jefferson-Henrique/GetOldTweets-python) which scrapes the Twitter Search browser for tweets containing the MeToo hashtag. At the time of use, I need to make changes to two lines of the code to retrieve the author's username as noted in the *issues* of the repository. With the usernames, I query the Official Twitter API which returns their user geolocation strings.

2. I use a series of hard-coded rules to parse the various user-input geolocations into a standardised U.S. city-state format (e.g. Philadelphia, Pennsylvania). I first retain only characters in a string that are ASCII characters, so that non-English and symbols are removed. After retaining only ASCII characters, 87'123 geolocation strings have a character length of 7 or less, indicating a sizeable number of Twitter users key-in non-ASCII.

3. I then check whether the geolocation string can be unambiguously identified as a non-U.S. country. If so, these are filtered out immediately. Using the ISO-3166 country names and codes, 89'115 (16% of 520'513) of the geolocation strings are immediately identified as Twitter users who list a non-U.S. country as their location.

4. For the remaining geolocation strings, I check if they can be identified as a U.S. city-state by searching for both state names and postal codes as well as city names within the string. Pseudo-code listing 1 provides the specific hard-coded rules used. The set of rules allows me to successfully parse 130'433 (25% of 520'513) geolocations into a standard U.S. city-state. A relatively small percentage of geolocation strings, 19'590 or 3.8%, is stated as the United States, but omits information about the state, the city, or both.

5. Finally, I match the tweets by U.S. city-state to their primary counties using the *United States Cities Database*. The primary counties are defined by the U.S. Geological Survey, which takes the centroid of a city and then recording the county in which the centroid lies.

Pseudocode 1: Parsing Geolocation

```
foreach geoloc(ation string) do
    if comma not in geoloc then
        /* [Step 1] Check if unambiguously a non-U.S. country                          */
        if len(geoloc)==2 then
            check if geoloc matches a non-U.S. country using ISO alpha-2 code
        else if len(geoloc)==3 then
            check if geoloc matches a non-U.S. country using ISO alpha-3 code
        else
            check if geoloc matches a non-U.S. country using ISO country name name
        if not unambiguously non-U.S. country in [Step 1] then
            /* [Step 2] Try geoloc string as U.S. city w/o state info.                 */
            try geoloc as a city named after state (e.g. 'utah' as Utah City, Utah)
            if that fails then
                try geoloc as a uniquely named U.S. city (e.g. 'chicago' as Chicago City in Illinois)
        if still not identified as a U.S. city-state in [Step 2] then
            /* [Step 3] Try geoloc string as U.S. city with state info.                */
            check if a comma is implied in either order (e.g. 'philadelphia pa' and 'pa philadelphia' as
              Philadelphia City, Pennsylvannia)
    if comma in geoloc then
        /* [Step 4] Check if unambiguously a non-U.S. country                          */
        check if one side of comma is unambiguously a non-U.S. country as in [Step 1] (e.g. 'beunos aires,
          argentina' should be filtered out)
        if not unambiguously a non-U.S. country then
            /* [Step 5] Try as a U.S. city-state                                       */
            if one side of comma in geoloc has len==2 then
                use as State postal code and the other side as city (e.g. 'avon, al' as Avon City, Alabama)
            else
                try one side as a State name and the other as a city name (e.g. 'avon, alabama' and 'alabama,
                  avon' as Avon City, Alabama)
        if still not identified as U.S. city-state then
            /* [Step 6] Try one side as city-state and the other an indicator of the States (e.g.
               'us', 'usa', 'united states', 'united states of america'                */
            if one side is indicator of the U.S. then
                try other side as city named after state (e.g. 'utah, usa' as Utah City, Utah)
                if that fails then
                    try geoloc as a uniquely named U.S. city (e.g. 'chicago, united states' as Chicago City in
                      Illinois)
```

Table A1

Examples of Parsing Twitter User Geolocation

User Geolocation	State	(Primary) County
nomadic	—	—
sandy oaks, tx	Texas	Bexar
los angeles, ca	California	Los Angeles
calcinato, lombardia	—	—
pensacola, fl	Florida	Escambia
london, england	—	—
victoria, bc, canada	—	—
virginia	—	—
washington, dc	District of columbia	District Of Columbia
dallas, tx	Texas	Dallas
south ca	—	—
united states	—	—
michigan, usa	—	—
bordeaux, aquitaine	—	—
oxford, ms	Mississippi	Lafayette
chicago	Illinois	Cook
port townsend, wa	Washington	Jefferson
ut ,	—	—
namak haram in pakistan	—	—
lagos, nigeria	—	—
boston, ma	Massachusetts	Suffolk
grittydelphia via la,nyc,gb	—	—
pakistan	—	—
oakland, ca	California	Alameda
united states	—	—
st louis, mo	Missouri	St. Louis (City)
kitchener, ontario	—	—
san francisco, ca	California	San Francisco
stanford, ca	California	Santa Clara
probably on the floor sumwhere	—	—
chicago, il	Illinois	Cook
houston, tx	Texas	Harris
micromsmemumbaiwala	—	—
mother earth	—	—
houston, tx	Texas	Harris
cleveland, tn	Tennessee	Bradley
oregon, usa	—	—
tuscaloosa	Alabama	Tuscaloosa
new york	New york	New York
provo, ut	Utah	Utah
united states	—	—
grand rapids, mi	Michigan	Kent
the village	Oklahoma	Oklahoma
san francisco	California	San Francisco
murcia, espana	—	—
mount greenwood, chicago	—	—
morgantown, wv	West virginia	Monongalia
las vegas, nv	Nevada	Clark
new jersey, usa	—	—
whalley, bc	—	—

Notes—This Table provides 50 examples of parsing twitter users' geolocation. *User Geolocation* column is the self-declared geolocation of users. *State* column is the identified State in the U.S., and the *(Primary) County* column is the identified U.S. county based on the city-state. Primary Counties are identified using the *United States Cities Database* from `https://simplemaps.com/data/us-cities` where primary counties of cities are identified by the U.S. Geological Survey and U.S. Census Bureau by taking the centroid of a city and then recording the county in which the centroid lies.

A.2 Extra Figure and Tables

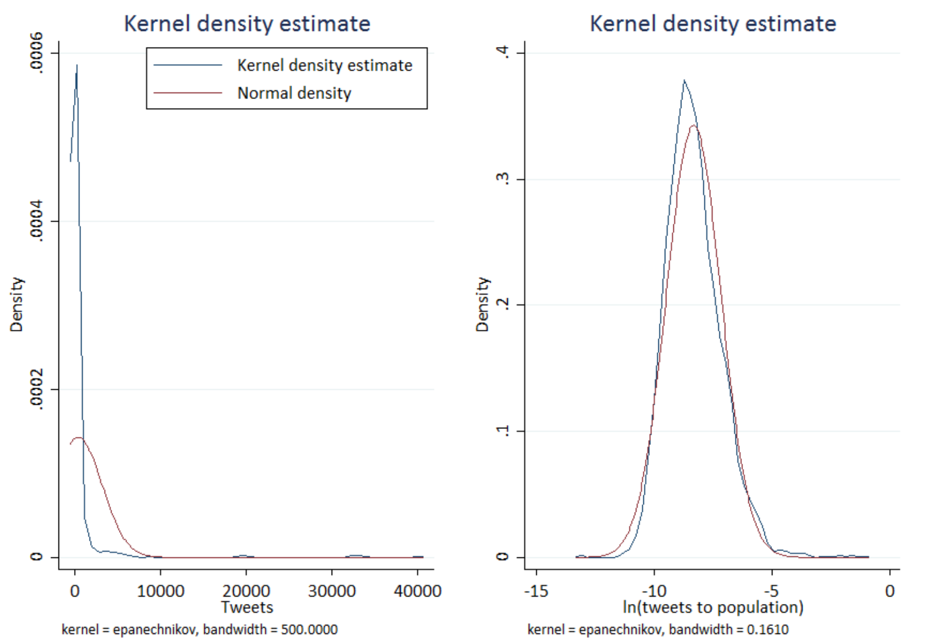

Figure A1: Distribution of MeToo Tweets, by Counties

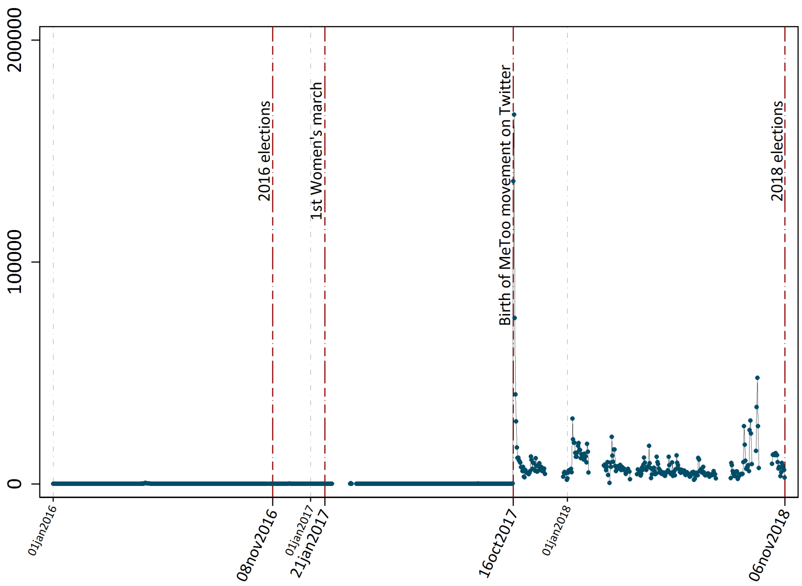

Figure A2: Extended Timeline of MeToo Tweets, Levels

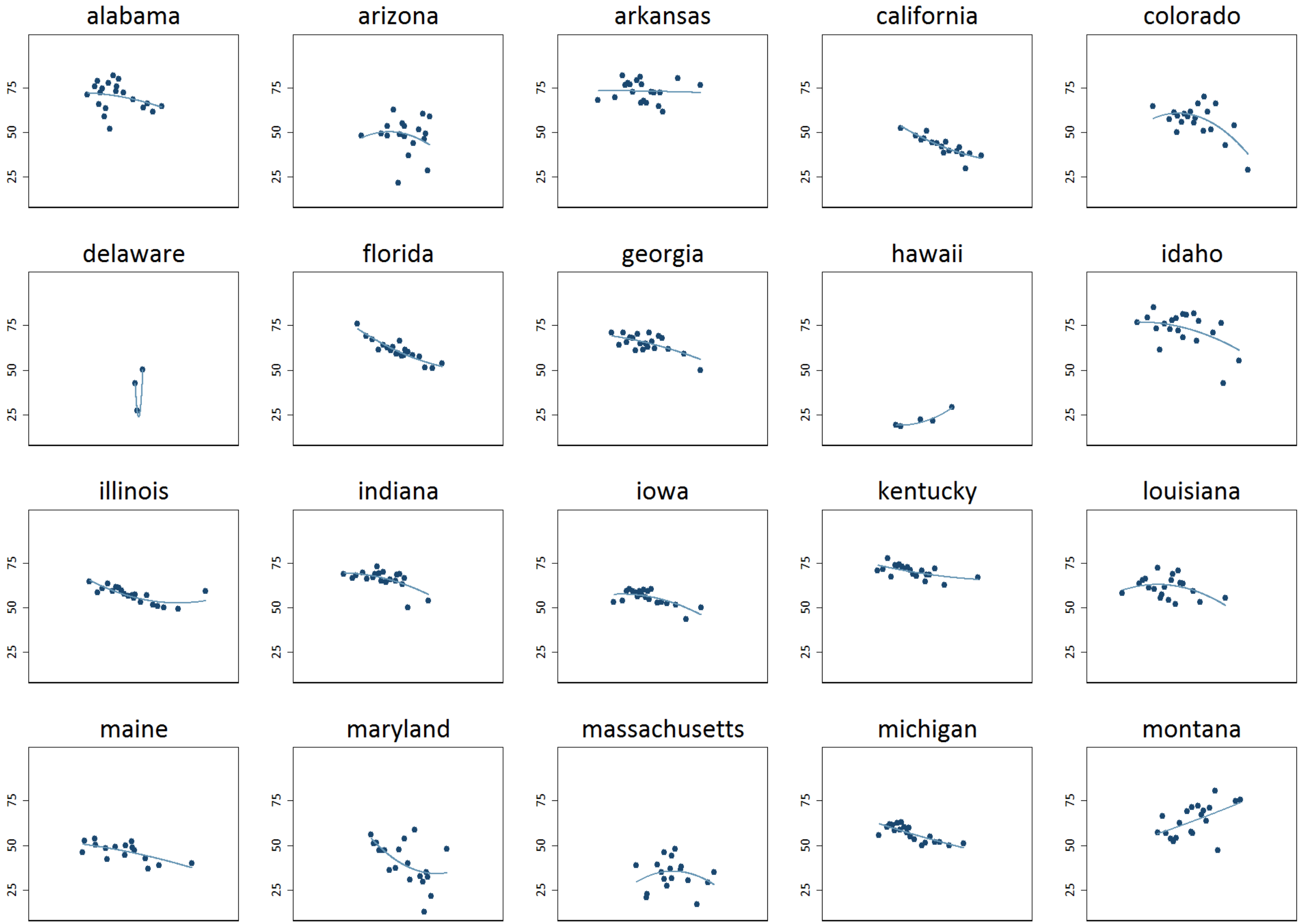

Figure A3: Correlations of Tweets and Republican Vote Share, by State (Part 1)

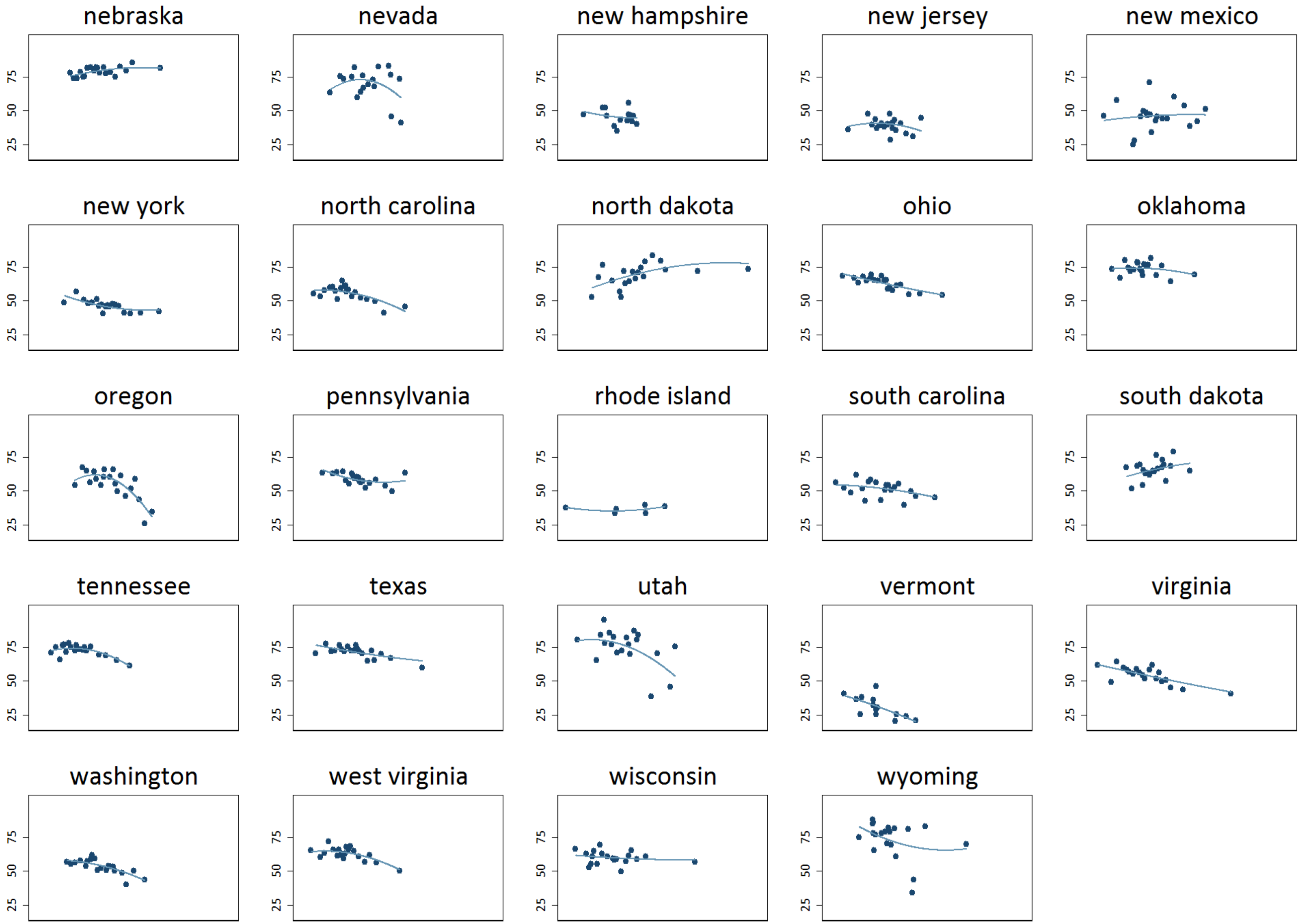

Figure A4: Correlations of Tweets and Republican Vote Share, by State (Part 2)

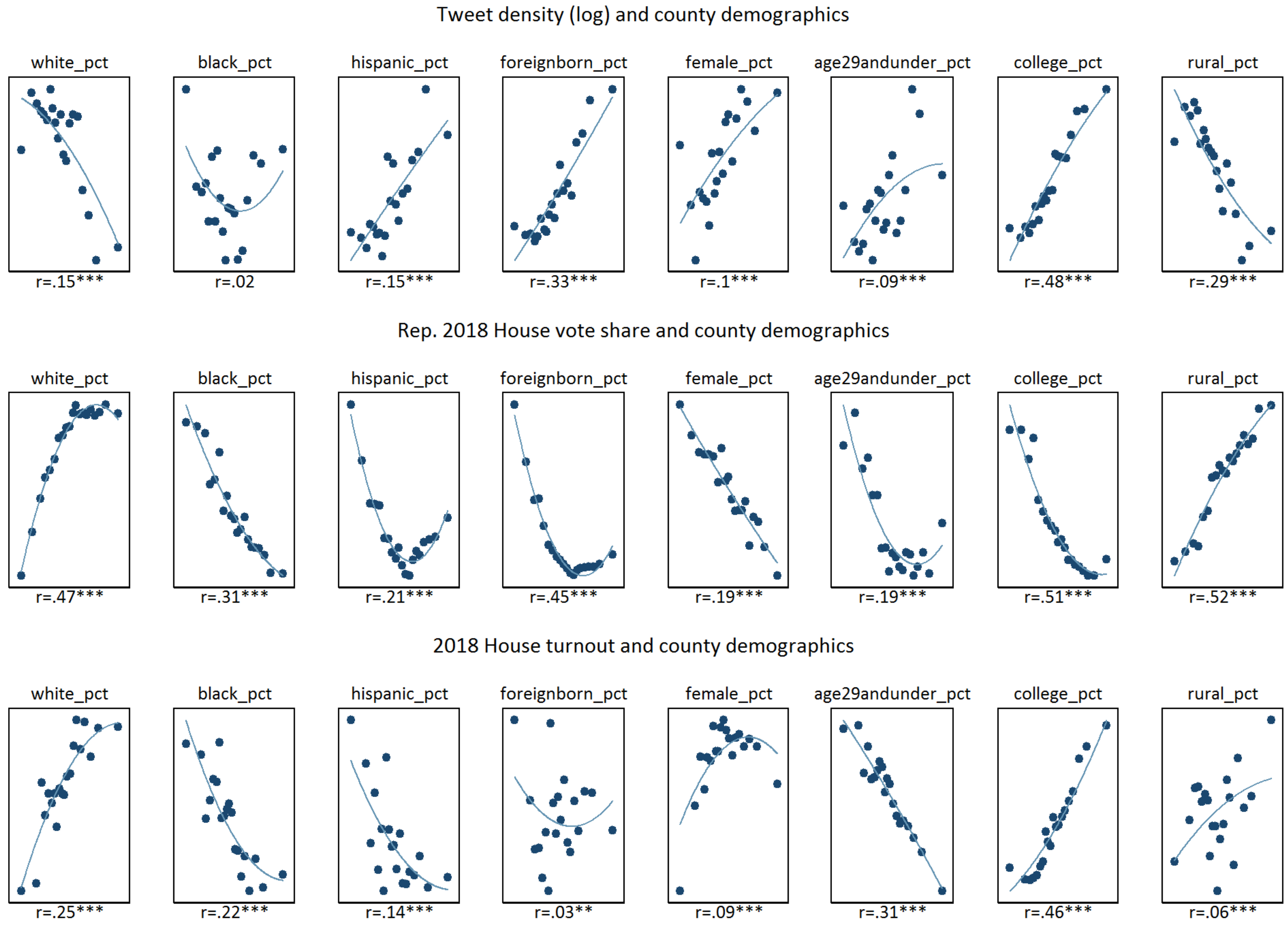

Figure A5: Correlation (Binned Scatters) between County Demographics, Tweets, and 2018 House Elections

Table A2
Selection of Women Candidates into Districts

	Dep. var. are indicators for				
	At least 1 woman candidate	Exactly 1 woman candidate	H2H man-woman main party	At least 1 woman challenger	At least 1 main-party woman challenger
	(1)	(2)	(3)	(4)	(5)
Log tweets density	−0.009	−0.029*	−0.058	0.005	−0.017
	(0.067)	(0.016)	(0.057)	(0.072)	(0.064)
Past Electoral controls					
House Rep. vote share in 2016	−0.001	−0.002	0.002	−0.000	0.001
	(0.004)	(0.002)	(0.005)	(0.005)	(0.005)
House turnout 2016	0.006	−0.002	0.007	0.007	0.007
	(0.006)	(0.003)	(0.006)	(0.007)	(0.006)
Pres. Rep. vote share in 2016	0.008	0.006***	0.004	0.006	0.005
	(0.007)	(0.002)	(0.009)	(0.008)	(0.009)
Pres. Rep. vote share change (2012–16)	−0.013	−0.003	−0.024	−0.007	−0.014
	(0.016)	(0.008)	(0.015)	(0.016)	(0.013)
Pres. turnout 2016	−0.001	−0.003	−0.005	−0.001	−0.000
	(0.014)	(0.006)	(0.015)	(0.015)	(0.015)
Political Seat controls					
Open seat	0.337***	0.010	0.252***	0.445***	0.477***
	(0.109)	(0.069)	(0.089)	(0.110)	(0.102)
Incumbent is woman	0.576***	−0.137***	0.551***	−0.146	−0.040
	(0.080)	(0.037)	(0.147)	(0.140)	(0.077)
Incumbent is Republican	0.256***	−0.026	0.175*	0.361***	0.341***
	(0.079)	(0.044)	(0.094)	(0.067)	(0.064)
Incumbent is Rep. woman	−0.072	0.149***	−0.735***	0.369*	0.301**
	(0.115)	(0.055)	(0.209)	(0.185)	(0.133)
State fixed effects	*X*	*X*	*X*	*X*	*X*
Census Control	*X*	*X*	*X*	*X*	*X*
F-test: County census = 0	6***	9.8***	4.54***	2.65**	1.69*
R^2	0.280	0.255	0.221	0.235	0.243
Probability (Unconditional)	0.541	0.067	0.405	0.430	0.376
N	388	388	388	388	388

Notes—Observations are House congressional districts. Results are estimated using the linear probability model. Dependent variable in column (1) is the dummy for at least one woman candidate in the district; in column (2) it is the dummy for exactly one woman candidate; in column (3) it is a dummy for when there is a head-to-head between a man and woman candidate from the major party; in column (4) it is a dummy for at least one woman candidate who is a challenger; and in column (5) it is a dummy for at least one woman candidate who is a challenger from one of the two major parties. Census controls are aggregated from the county to the district level. Observations weighted by the total votes cast in the 2016 Presidential election. Robust standard errors in parentheses are clustered at states.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A3

FULL REPORT OF INTERACTED COEFFICIENTS, FOR PARTY AND GENDER

	All-party	Two-party
	(1)	(2)
Rep. woman × (Log tweet density)	−0.707	−0.472
	(0.724)	(0.713)
Dem. woman × (Log tweet density)	−0.655***	−0.930***
	(0.253)	(0.287)
Rep. man × (Log tweet density)	0.300	0.408
	(0.235)	(0.255)
Dem. man × (Log tweet density)	−0.029	−0.439
	(0.354)	(0.431)
Rep. woman × (Pres. 2016 Rep. vote share)	0.330	0.543*
	(0.298)	(0.281)
Dem. woman × (Pres. 2016 Rep. vote share)	−0.342**	−0.483***
	(0.149)	(0.137)
Rep. man × (Pres. 2016 Rep. vote share)	0.401***	0.623***
	(0.130)	(0.099)
Dem. man × (Pres. 2016 Rep. vote share)	−0.446***	−0.572***
	(0.140)	(0.138)
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.023	−0.027
	(0.030)	(0.029)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.037***	0.047***
	(0.014)	(0.013)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.021**	−0.022**
	(0.009)	(0.009)
Dem man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.014	0.027*
	(0.014)	(0.015)
Control variables		
Candidate fixed effects	X	X
2016 House & 2012–16 Pres. election	X	X
County census demographics	X	X
Racial & gender voting	X	X
Main-party candidates only		X
R^2	0.977	0.952
N	8470	6234

Notes—This Table reports the full coefficients of the interaction between party, gender, log tweet density, and the 2016 presidential Republican vote share. The coefficients here corresponds column (4) of Table III.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A4

Additional Robustness Checks

	Additional robustness check for Column (4) of Table III					
	(1)	(2)	(3)	(4)	(5)	(6)
Rep. woman $\times$ τ $\times$ (Pres. 2016 Rep. vote share)	-0.016	-0.027	-0.027	-0.027	-0.024	-0.058
	(0.032)	(0.029)	(0.027)	(0.027)	(0.030)	(0.056)
Dem. woman $\times$ τ $\times$ (Pres. 2016 Rep. vote share)	0.037^{***}	0.047^{***}	0.047^{***}	0.047^{***}	0.049^{***}	0.048^{**}
	(0.012)	(0.014)	(0.014)	(0.014)	(0.015)	(0.023)
Rep. man $\times$ τ $\times$ (Pres. 2016 Rep. vote share)	-0.016^{*}	-0.022^{**}	-0.022^{***}	-0.022^{***}	-0.023^{**}	-0.018^{*}
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Dem. man $\times$ τ $\times$ (Pres. 2016 Rep. vote share)	0.020	0.027^{*}	0.027	0.027^{*}	0.023	0.039^{**}
	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)	(0.018)
Control variables						
Candidate fixed effects	X	X	X	X	X	X
2016 House & 2012–16 Pres. election	X	X	X	X	X	X
County census demographics	X	X	X	X	X	X
Racial & gender voting	X	X	X	X	X	X
Main-party candidates only						
General log(tweets) - log(population)	X					
Drop Hawaii		X				
Two-way cluster Candidate and county			X			
Two-way cluster Candidate and District-county				X		
MeToo tweets without other hashtags					X	
Std. dev. tweets < 90th percentile						X
R^2	0.953	0.952	0.951	0.951	0.952	0.960
N	6234	6224	6122	6122	6234	5592

Notes—This Table presents additional robustness checks for column (4) Table III. In column (1), the specification is more general, with log(tweets) and log(population) entering the model separately so that their coefficients are allowed to differ. In column (2), observations from Hawaii are dropped. Columns (3) and (4) adjust standard errors by two-way non-nested clustering of the house candidates and county. In column (5), the tweets measure is computed using only tweets with a single (the MeToo) hashtag. In column (6), only districts where the standard deviation in the MeToo tweets is lower than the 90th percentile are included. In column (1) the reported coefficient is for log(tweets), in columns (2)–(6) the tweets measure is the log tweet density measure—log(tweets/population). All controls are otherwise the same, and robust standard errors in parentheses are otherwise clustered by candidates.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table A5

THE EFFECT OF THE METOO MOVEMENT ON TURNOUT (PLACEBO—CHANGE IN TURNOUT PRESIDENTIAL ELECTION 2012–16)

	Measure of county-level MeToo movement (τ) is			
	ln(No. of tweets divided by population)		ln(No. of tweets)	
	(1)	(2)	(3)	(4)
τ	0.0006	-0.0032	0.0019**	0.0033
	(0.0008)	(0.0057)	(0.0009)	(0.0034)
Pres. 2016 Rep. vote share		-0.0015*		-0.0018**
		(0.0008)		(0.0007)
$\tau \times$ (Pres. 2016 Rep. vote share)		0.0001		-0.0000
		(0.0001)		(0.0001)
District fixed effects	X	X	X	X
Census Control	X	X	X	X
F-test: County census = 0	$F = 27.23$***	$F = 22.49$***	$F = 20.98$***	$F = 21.16$***
R^2	0.6752	0.6786	0.6759	0.6791
N	2648	2648	2648	2648

Notes—Observations are at the county level. The dependent variable is the log of total county votes cast in the 2016 Presidential elections minus the same variable for the 2012 Presidential elections. In columns (1)–(2), the measure of the MeToo movement is the log of county-level MeToo tweets divided by county population; in columns (3)–(4) the measure is the log of county-level MeToo tweets. Pres. 2016 Rep. vote share is the two-party county-level vote share of the Republican candidate in the 2016 presidential election. County census controls for demographics from the ACS 5-year estimates for 2012–16 also includes voting-aged population in this Table. Controls also include the 2008–2012 presidential elections turnout and Republican vote share. Robust standard errors in parentheses are clustered by districts.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A6

THE EFFECT OF METOO ON INDIVIDUAL VOTING (VOTER DATA)

	$\mathbb{1}$(Voted Republican) in 2016	$\mathbb{1}$(Voted Republican) in 2018	Change in vote from Dem. to Rep.
	(1)	(2)	(3)
Log tweet density	-0.012***	-0.009***	-0.005**
	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(Always vote for Democrats)	-0.077***	-0.077***	0.003
	(0.012)	(0.012)	(0.011)
$\mathbb{1}$(Always vote for Republicans)	0.066***	0.092***	-0.022***
	(0.009)	(0.013)	(0.007)
Control variables			
Individual characteristics	X	X	X
Voting history & tendency	X	X	X
Political interest & knowledge	X	X	X
F-test: Individual characteristics = 0	$F = 4.66$***	$F = 1.78$**	$F = 1.38$*
F-test: Voting history & tendency = 0	$F = 2736.44$***	$F = 2405.58$***	$F = 5.04$***
F-test: Political interest & knowledge = 0	$F = .5$	$F = .91$	$F = .78$
R^2	0.723	0.764	0.033
N	6020	3466	3204

Notes—Observations are individual respondents in the Democracy Fund VOTER (Views of the Electorate Research) survey. The dependent variable in column (1) is a dummy for whether the respondent voted Republican in the 2016 Presidential. The dependent variable in column (2) is a dummy for whether the respondent *would* have voted Republican for Congress in 2018 (recorded in April). Base category is to vote Democrat. The dependent variable in column (3) captures whether the respondent changes vote from 2016–18: 1 if vote changes from Democratic to Republican, 0 if no change, -1 if from Republican to Democratic party. All regressions control for individual characteristics including gender, race, education, employment, birth cohort (by decade), income, marital status and number of children. Voting history & tendency controls include which party the individual would have for congress and president in 2012, and an indicator for whether the individual always for for the same party. Political interest and knowledge controls for the level of interest and knowledge the individual has in politics and current affairs. Robust standard errors clustered by counties.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A7

The Mediated Effect of the MeToo Movement, 2016 House Elections

	All-party	Two-party	
	(1)	(2)	(3)
	A. Gender dimension only		
Woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.015	0.018	−0.011
	(0.014)	(0.015)	(0.017)
Man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.008	0.009	0.016**
	(0.006)	(0.007)	(0.008)
	B. Party dimension only		
Rep. × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.015*	−0.018**	−0.012
	(0.008)	(0.008)	(0.010)
Dem. × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.032***	0.040***	0.040***
	(0.010)	(0.009)	(0.011)
	C. Party & Gender		
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.039	−0.044	−0.057
	(0.040)	(0.039)	(0.038)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.040**	0.041**	0.009
	(0.017)	(0.016)	(0.020)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.014	−0.016*	−0.011
	(0.009)	(0.009)	(0.010)
Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.031***	0.040***	0.049***
	(0.011)	(0.011)	(0.013)
Control variables			
Candidate fixed effects	*X*	*X*	
District fixed effects			*X*
2008–12 Pres. election	*X*	*X*	*X*
County census demographics	*X*	*X*	*X*
Racial & gender voting	*X*	*X*	*X*
Main-party candidates only		*X*	*X*
N	7822	6055	6055

Notes—The dependent variable is the 2016 house candidate vote share at the district-county level. Tweet density is the (natural) log of MeToo tweets in 2018 divided by county population. Column (1) reports the results for the full all-party sample; column (2) reports the results for the main-party sample and uses two-party vote shares on both sides of the equation. Past electoral results include the 2008 and 2012 presidential Republican vote share. All controls are otherwise the same as in Table III. Robust standard errors in parentheses are clustered by candidates.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table A8

Change in Republican Vote Share, District-County Level (Log Tweets)

	Change in *house* Republican vote share between 2016 and 2018				Placebo specifications	
	Change in Republican all-party vote share		Change in Republican two-party vote share		Change in *presidential* Republican vote share between 2012 and 2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Log tweets × (Pres. 2016 Rep. vote share)	−0.0420***	−0.0407***	−0.0183***	−0.0170***	0.0001	
	(0.0042)	(0.0041)	(0.0043)	(0.0042)	(0.0018)	
Log tweets × (Pres. 2012 Rep. vote share)						0.0003
						(0.0019)
Log tweets	0.1642	0.1976	0.0916	0.1181	−0.1080**	−0.1520
	(0.1827)	(0.1553)	(0.1982)	(0.1679)	(0.0504)	(0.1120)
Change in log(total House votes) 2016–18		−2.8503*		−2.9637*	−0.0090	−0.6971**
		(1.5772)		(1.6704)	(0.0977)	(0.3007)
Change in log(total Pres. votes) 2012–16					−3.1550*	−1.8770
					(1.9132)	(1.5940)
Control variables						
District fixed effects	X	X	X	X	X	X
Past electoral controls	X	X	X	X	X	X
County census demographics	X	X	X	X	X	X
R^2	0.8954	0.8997	0.9061	0.9107	0.8730	0.9084
N	3102	3102	3102	3102	3102	3102

Notes—This Table replicates the regressions in Table VII, except that log tweets are used instead of log tweet density (log of tweets divided by county population). All specifications are otherwise the same. Robust standard errors in parentheses are clustered by the 388 U.S. House congressional districts.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table A9
Additional Effects by State and District

	Differences by State I == 1 if State has				Differences by Districts I == 1 if District has	
	Two Rep. senators	Both Rep. & Dem. senators	No senate elections	Battleground States	Head-to-head bw. man & woman	Low Margin
	(1)	(2)	(3)	(4)	(5)	(6)
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.020	−0.020	−0.021	−0.029	−0.040	−0.026
	(0.027)	(0.027)	(0.029)	(0.029)	(0.027)	(0.029)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.046***	0.046***	0.047***	0.046***	0.034**	0.043***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.023***	−0.023***	−0.023**	−0.021**	−0.020**	−0.021**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.025*	0.025*	0.028*	0.024	0.025*	0.027*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Additional differences by State/District						
I × Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.019*	−0.019*	−0.018*	0.007	0.010	−0.008
	(0.010)	(0.010)	(0.010)	(0.016)	(0.013)	(0.012)
I × Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.004	0.004	−0.003	0.001	0.014	0.011**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.012)	(0.006)
I × Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.001	0.001	0.001	−0.002	−0.007*	−0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
I × Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.009	0.009	−0.003	0.005	−0.003	0.012*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Control variables						
Candidate fixed effects	X	X	X	X	X	X
2016 House & 2012–16 Pres. election	X	X	X	X	X	X
County census demographics	X	X	X	X	X	X
Racial & gender voting	X	X	X	X	X	X
Main-party candidates only	X	X	X	X	X	X
R^2	0.952	0.952	0.952	0.952	0.953	0.952
N	6234	6234	6234	6234	6234	6234

Notes—This Table replicates columns (3)–5) of Table III, except that an additional interaction is entered into the model to capturing any differences of the MeToo effect by state or district. In column (1), the additional interaction is a dummy for states where both senators are Republican; in column (2), it is for states where the senate is split; in column (3), it is in states where there were no senate elections in 2018; in column (4), it is for battleground states defined as states with less than a 10% margin in the 2016 presidential elections; in column (5), it is for districts with a head-to-head between a woman and man candidate from the main parties in the 2018 House elections; and in column (6), it is for districts where the winning margin is less than 5% in the 2018 House elections. All other controls are the same. Robust standard errors in parentheses are clustered by candidates.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.