Deconstructing the MeToo movement and the blue wave in the 2018 house elections*

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Abstract

At the peak of the #MeToo movement in 2018 is the historical performance of women candidates in the 2018 midterm elections. Using geocoded #MeToo tweets and exploiting cross-county variation at the house candidate level, this study reveals that the MeToo movement did not led to higher vote shares for Democratic women candidates. Instead, I find that the more likely channel through which the Democratic party benefited is through active political machinations via the selective standing of women challengers and the turning out of voters. In Republican men incumbent districts, women challengers are more likely to run if there is high MeToo pressure. In counties with high support for the Republican president, there is higher turnout with higher MeToo pressure. These findings suggest that political agents do not remain passive when faced with grassroots movements but actively exploit them to benefit.

Keywords: Protest; Social media; Elections; Voting Behavior

JEL: D71; D72; P48

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1 Introduction

In 2018, the anti-sexual misconduct MeToo movement peaked with the help of grassroots-driven social media activity. The movement was more than window dressing since it gave traction to sexual harassment policies in Congress (North 2019). These include bills that limit non-disclosure agreements in cases of sexual misconduct (Tippett 2018b). By its peak, and right before the 2018 midterm elections, the movement precipitated into one that was generally favorable towards the Democratic party, against the Republican party, and against then-incumbent Republican President Donald Trump.

Occurring right at the peak of the MeToo movement, the 2018 US midterm elections saw women candidates achieve historical gains in Congress. 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 a historic 235 women candidates, with a historical 102 of them winning, where most (89 of the 102) ran under the Democratic banner (Center for American Women and Politics 2018).

The combination of these two facts led to assertions that the 2018 elections were a #MeToo elections (e.g., Deckman 2018; Peaker 2018; Tippett 2018a; Thomsen and King 2020), one where women and Democratic candidates rode on the general 2018 context and the MeToo zeitgeist for political advantages. This potentially leads to legislative changes since higher women representation changes legislative dynamics in Congress (as in Ban et al. 2022).

This study examines this assertion in the 2018 midterm house elections. Unpacking how and the extent to which the MeToo movement is linked to candidate-level vote share, turnout, and candidacy choices clarifies how political agents exploit grassroots social media movements to their advantage.

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

To estimate the level of MeToo support, I introduce a novel panel data based on geocoded MeToo tweets from the social media platform Twitter. I combined these tweets, which vary at the county level within the congressional electoral districts, with individual characteristics of the electoral candidates, the 2018 house election returns (MIT Election Data and Science Lab 2018a,b), and county-level demographics. I use the Democracy Fund Voter Study Group 2018 survey and assert that the MeToo tweets indeed capture anti-sexual harassment and the political parties associated to it—counties with more geocoded MeToo tweets have more individuals with attitudes in the spirit of the MeToo movement. I thus use the MeToo tweets as a measure of support for the MeToo movement.

Using three levels of analyses, this study examines whether and how the MeToo movement is connected to the historical performance of Democratic women candidates in 2018. The first approach tests whether county-level variation in MeToo support is tied to candidates' vote share within the districts they stand in. Here, I apply rigorous methods to ensure that a negative finding is not the result of an oversight in the modeling process. I also perform tests revealing how political agents engage the movement by campaigning more vigorously in key places and strategically placing candidates.

In the first analysis, to test whether Democratic women candidates benefited by getting more vote shares in counties with higher MeToo pressure, I estimate a difference-in-differences specification. I regress candidate-level vote shares in counties on the (i) county-level variation in MeToo tweets and (ii) the party-gender variation of candidates. The findings are nuanced. I find a systematic correlation of the MeToo support on Democratic women vote share, only when conditional on counties with high existing Republican support. Introducing an additional interaction term for the 2016 Presidential elections vote share of the Republican candidate (Donald Trump, more on his involvement in note 12) reveals 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. In comparison, Republican men incur a 0.45 percentage point disadvantage.

The biggest caveat, however, is from the 2016 House elections. I use the candidate returns from the 2016 elections, combined with the 2018 MeToo tweets, and estimate the same specification. The same finding of a Democratic woman candidate advantage can be traced back to the 2016 House elections using the MeToo tweets in 2018, suggesting that the findings reflect temporal trends in voting. Democratic women candidates are, therefore, unlikely to have passively benefited from the 2018 MeToo movement in terms of higher vote shares in counties with high MeToo pressure.

In light of this, I turn to more nuanced tests in the second and third analyses to shed more light on the political economy mechanisms through which political agents actively used the MeToo movement to their advantage. Since the 2018 house elections recorded historical numbers in turnout, I test and find that counties with high support for the 2016 Republican presidential candidate and with high support for the MeToo movement have higher turnout. For a one standard deviation increase in the tweets, a ten percentage point increase in support for the Republican candidate is associated with a 1.17% ($p < 0.05$) increase in turnout. A falsification test using the 2012–16 increase in turnout for the presidential elections yield no such finding. This points to how political agents likely campaigned harder in places with higher support for the movement.

To further deconstruct and, at the same time, contextualize how the movement potentially drove the Democratic gains in the 2018 house elections, I examine the variation in non-incumbent Democratic women candidacy across districts. More women in Congress can lead to changes in congressional discussions and tangible legislative changes (Ban et al. 2022). Yet women are traditionally underrepresented in politics because they are less likely to run (e.g., Thomsen and King 2020). The Democratic gains in 2018, largely driven by gains by the non-incumbent Democratic candidates, subvert this trend. I test and find evidence that non-incumbent women from the Democratic party are more likely to challenge when the incumbent is a Republican man in counties with higher support for the MeToo movement. Perhaps of surprise is the finding that non-incumbent women from the Democratic party are more likely to challenge when the incumbent is a Democratic man in counties with greater measured MeToo movement. The latter case appears to be more isolated since they are related to only six districts, with four of them part of "The Squad"—a group of Democratic members known for being in the left wing of the Democratic party and for being members of minority groups. The former case, however, where non-incumbent Democratic women candidates challenged a Republican incumbent man, suggests that what we learn about candidates capitalizing on the grassroots protest movement is more generalizable to other movements and elections. From the 2018 house returns, I identify 17 such districts where a non-incumbent Democratic woman candidate successfully unseat an incumbent Republican man.

Overall, the lack of credible evidence that candidates benefit in counties with high geolocated MeToo tweets suggests that the Democratic gains we observe in the 2018 house elections did not come from political candidates behaving passively. More likely is that a subset of non-incumbent Democratic candidates catch the winds of change in the general context of 2018—among others, the election of Donald Trump, the supreme court appointment of Brett Kavanaugh, and the general inertia of anti-sexual harassment bills in Congress (more details in Section 3)—and capitalized accordingly.

The interpretation that legislators, or at least potential candidates, actively campaigned by pivoting on the movement is consistent with the notion that political agents do respond to the voices of their constituencies on social media (e.g., Barberá et al. 2019). This squares with the results where there is systematically higher turnout in Republican counties with more MeToo support, which is likely through active campaigning of political agents. It is also consistent with the strategic and systematic challenge of non-incumbent women on both Republican and, to a smaller extent, Democratic men, incumbents in districts with high MeToo movement.

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).

This study contributes to the understanding of social media activity's role in politics and elections (as in Fujiwara et al. 2020), arising from what is essentially a grassroots movement on the 2018 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] The study by Fujiwara et al. 2020 in particular exploits early exposure to Twitter in the nascency and provides

[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.

one of the early pieces of evidence that social media can affect electoral outcomes—in favor of the Democratic party.

Another contribution is on how an independent media platform influences electorate behavior against the incumbent (Enikolopov et al. 2011; Fujiwara et al. 2020; 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 controlled nor have a formal political allegiance. The setting in this paper is similar, where the MeToomovement started as an independent grassroots movement. This paper also contributes to a growing literature on the effects of protest movements and rallies (Acemoglu et al. 2018; Campante et al. 2017; Feinberg et al. 2019; Kim 2022; Larreboure and Gonzalez 2021; Leon-Ablan and John 2022; Lilley and Wheaton 2019; Munger et al. 2019; Weiss et al. 2022).

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 Democraticcandidates.[3]

[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) ethnicity are systematically correlated to vote share. However, the variation it explains in vote share is small. This paper also bears some indirect non-experimental evidence of expressive voting, a behavior 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), which 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.

The rest of the paper is as follows. The next Section 2 describes the matching of Twitter data to US counties. Section 3 discusses legal and political implications of the MeToo movement. Section 4 analyses whether Democratic women candidates have higher vote shares in counties with higher MeToo support. Section 5 tests for evidence that Democratic women candidates, and the Democratic party in general, actively rode on the movement through strategic candidacy and targeted campaigning for turnout. Section 6 concludes.

2 Data

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

Geolocation of Twitter users. The tweets metadata includes usernames, which I use to query the Official Twitter API for user geolocation. The 1,915,322 tweets come from 700,891 usernames. Of the 700,891 usernames, 158,857 cannot be found

[4] The *GetOldTweets-python* library is written by Jefferson Henrique and is hosted at https://github.com/Jefferson-Henrique/GetOldTweets-python. I changed two lines of code, by necessity, to handle changes in the underlying browser's HTML formatting (at the time of writing) so that the Twitter username can be retrieved. The Official Twitter API has a 7-day limit on past tweets at the time of this writing. Under the hood, the third-party API scrapes 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.

[5] *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 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.

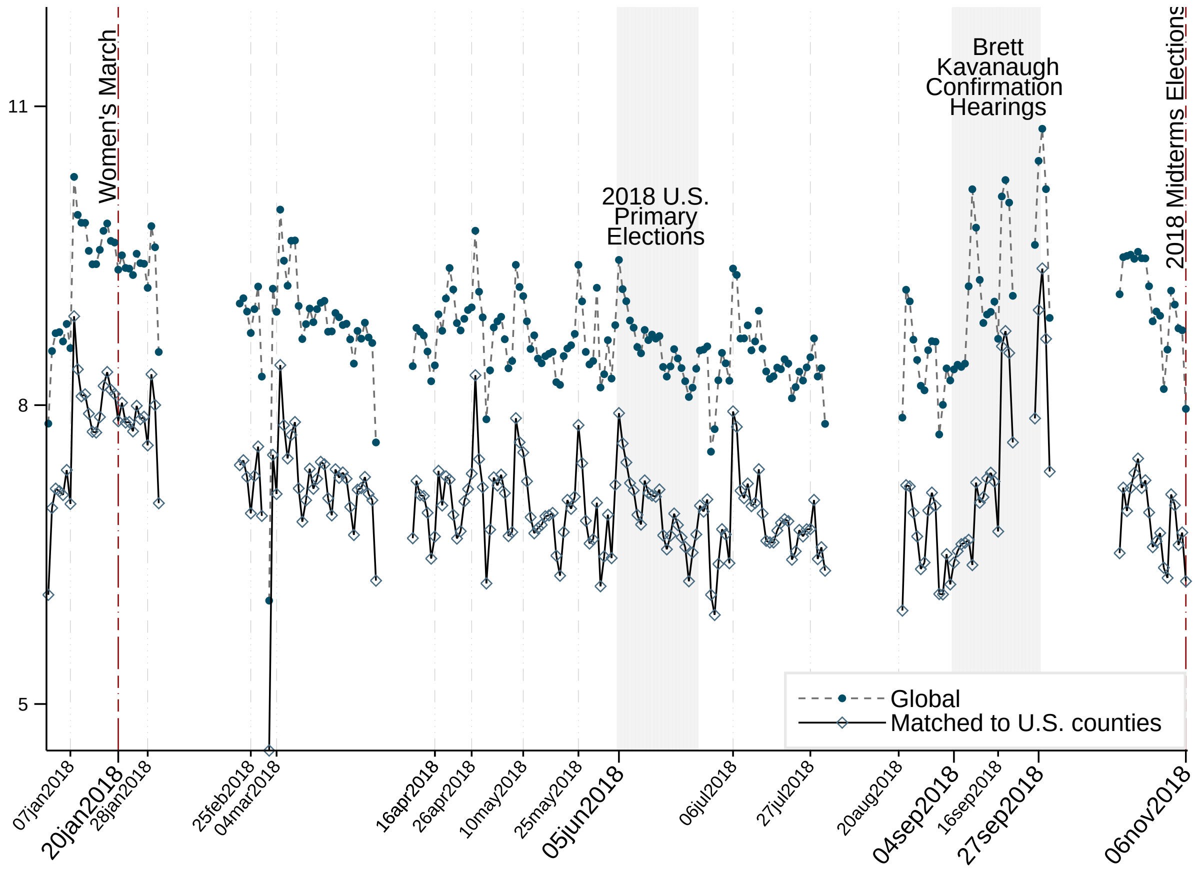

Figure I: Intensity of Tweets with MeToo Hashtag in 2018[5]

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 standardized formatting. To parse the user geolocation strings, I write a series of hard-coded rules to identify the US 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 US Geological Survey. Appendix A.1 provides more details. In the Appendix A.2, I combine the geocoded MeToo tweets together with the Democracy Fund Voter Study Group 2018 survey and assert that the MeToo tweets indeed capture general pro-women and anti-Republican senti-

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

ments. I argue that the MeToo tweets are unlikely to arise from disingenuous grassroots activity ("astroturfing"). I also show using the 2018 *VOTER* (Views of the Electorate Research) survey (Democracy Fund Voter Study Group 2018) that the geocoded MeToo sample correlates with county variations of attitudes towards sexism, sexual harassment, and disapproval of the Republican party's involvement in the MeToo movement. This finding is consistent with the literature where Twitter data can accurately capture protest movements on the ground (Sobolev et al. 2020).

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 ethnicity) 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) ethnicity is White, Black, Hispanic, or Other.[9]

County-level covariates. County demographics come from the ACS (American Community Survey) 5–year estimates for 2012–2016 and for 2015–2019. The 14 variables include population and voting population sizes, demographic composition by ethnicity, gender, age, foreign-born, 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

[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 patterns —people of the same type communicate more frequently and recently.

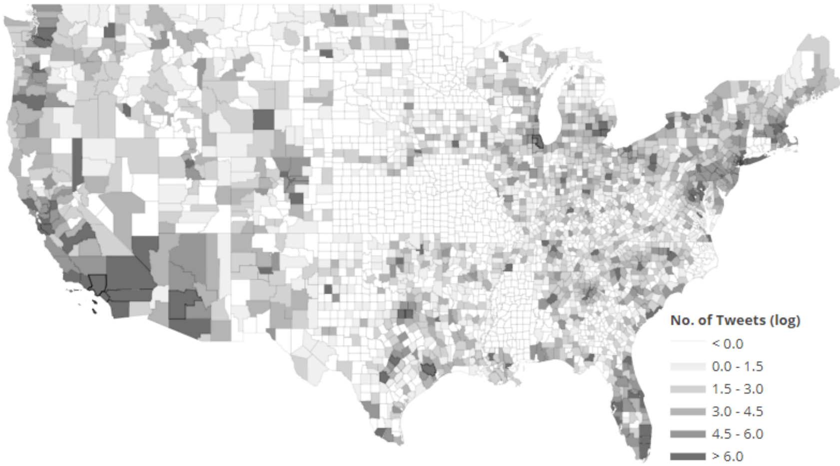

Figure II: GEOGRAPHICAL DISTRIBUTION OF METOO TWEETS IN 2018

least 200 kbps in at least one direction to the total number of households—for June 2017 come from the FCC (Federal Communications Commission).[10] For past elections, both the county-level 2016 House elections and Presidential elections data come from the *MIT Election Data and Science Lab* (MIT Election Data and Science Lab 2018a,b).

Summary. Figure I shows the intensity of the MeToo tweets throughout the year 2018 right up to the election on November 6. 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 candidates' vote share by state and county. The final sample is for 44 US 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.

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

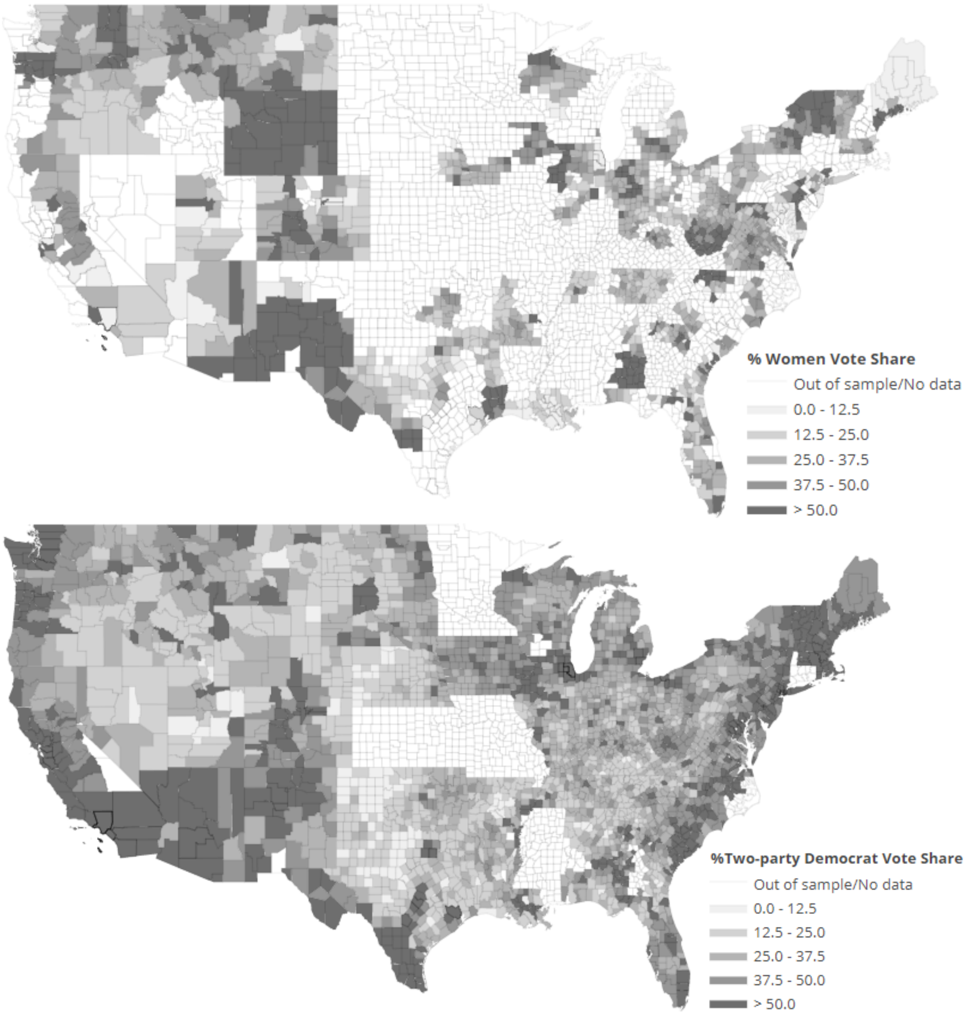

Figure III: Geographical Distribution of Women and Democratic Vote Share

3 Context and Implications of MeToo

3.1 Legal and Electoral Implications in the US

The MeToo Movement. The phrase "Me Too" began more than a decade ago, in 2006, on the Myspace social network. Around that time, Tarana Burke used it in her local community to encourage Black and Hispanic girls and other women to come forth with their accounts of sexual misconduct (Eisele et al. 2022; 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. What were once private experiences of sexual harassment by many people catalyzed into the public sphere via Twitter (Goenaga 2022). This forms the bedrock of the 2018 zeitgeist and spurs suggestions that the time has come for real change through legislation in Congress (e.g., Deckman 2018; Peaker 2018; Tippett 2018a; Thomsen and King 2020).

Legal Implications of the Movement. As implied, the MeToo movement, with widespread attention in social media, is more than just window dressing. First, the attention on sexual harassment issues has gained traction in Congress, with Democrats sponsoring the BE HEARD Act (Bringing an End to Harassment by Enhancing Accountability and Rejecting Discrimination Act) with bipartisan support to extend harassment protections to workers at small businesses and independent contractors (North 2019).[11] Second, courts tended to apply the *Faragher* defense—when employers can show they took reasonable measures to prevent or redress harassment—in favor of employers, and the MeToo movement may pressure courts to be more narrow on what they consider reasonable (Tippett 2018b). 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 (Tippett 2018b).

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 favorable judicial performance evaluation. 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 dates back to 1977 (Singer

[11] 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 2018b).

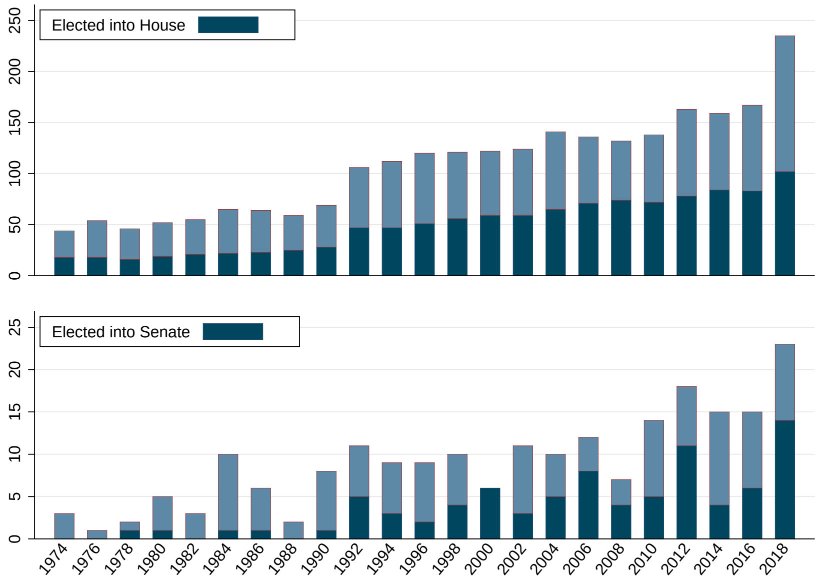

Figure IV: Women in Congress

2019).[12] [13]

Electoral Implications of the Movement? The media and other studies have suggested that the 2018 midterm elections were a "#MeToo election", where women candidates benefitted from the MeToo the movement (e.g., Deckman 2018; Peaker 2018; Tippett 2018a; Thomsen and King 2020). Voting more women into Congress, in particular, would help break the general inertia around the anti-sexual harassment bills (Tippett 2018a).

There appears to be some truth to this. Traditionally, women tend to be underrepresented in the running for political offices (e.g., Thomsen and King 2020). The 2018 elections subvert this trend. 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 (Center

[12] In states with the retention election system, nonpartisan commissions nominate qualified judicial candidates to the governor, who then appoints 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).

[13] In a similar turn of events, former Connecticut US 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.

for American Women and Politics 2018). According to Thomsen and King (2020), a notable number of these successful non-incumbent Democratic women candidates in 2018 are lawyers, which fits into the narrative of a greater need for legislative changes related to sexual misconduct.

Part of the general sense around 2018, before the midterm elections, is of a coming reckoning for outstanding issues. The nomination and confirmation hearings of Kavanaugh were a particularly salient and politically charged episode (Walsh 2018). 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, too, is entwined in the movement, having been accused of sexual harassment. There were women marches shortly after the 2016 Presidential election as an objection to Trump's election (note 5).

Even in the popular media, there are pieces of men caught in the MeToo wave and whose replacements are made up of women half the times (Carlsen et al. 2018). The implication is that there is public demand for women in positions that men traditionally held. Perhaps these include political offices. Some of these men brought down by the MeToo movement are indeed politicians who left their seats vacant until the 2018 midterms (Carlsen et al. 2018).

While purely descriptive, Figure V suggests a negative correlation between the MeToo movement and the house Republican vote share. The rest of the paper analyses more formally the extent to which the MeToo movement is linked to the Democratic gains in the 2018 house elections. Theoretically, the Democratic party could have benefited in a passive manner from the MeToo movement. This happens if Democratic women candidates get higher vote shares in counties because of the higher MeToo pressure. Section 4 put this to test. On the other hand, the link between the Democratic party and MeToo support (as seen in Figure V) may exist because of selective political machinations. This could come from the strategic standing of women candidates or from active campaigning to turn out voters. Sec-

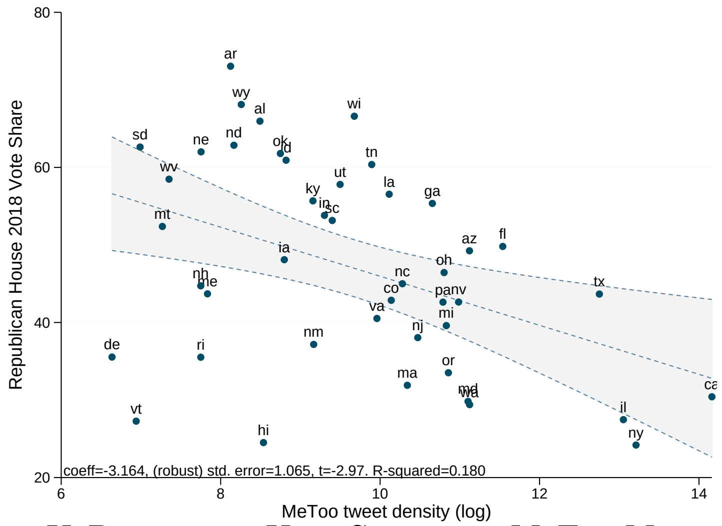

Figure V: REPUBLICAN VOTE SHARE AND METOO MOVEMENT

tion 5 tests this.[14]

4 Candidate Vote Share

4.1 Difference-in-Differences

To test the extent of a relationship between MeToo movement and political candidate-level returns at the 2018 House elections, the baseline empirical strategy I use is the difference-in-differences (DD) strategy. I compare returns for candidates based on the MeToo tweet density, which varies across counties, and the party-gender of candidates, which vary by candidate. Formally, I regress the vote share of individual candidates at the district-county level on the interaction of candidate party-gender and the density of the MeToo tweets at the county levels:

$$(1)\quad \nu_{icd} = \alpha + \beta^{RW} RW_i \tau_c + \beta^{DW} DW_i \tau_c + \beta^{RM} RM_i \tau_c + \beta^{DM} DM_i \tau_c + \text{Candidate}_i + \boldsymbol{\Delta}_1 \boldsymbol{\nu}^{\text{Rep., House}}_{c,2016} + \boldsymbol{\Delta}_2 \boldsymbol{\nu}^{\text{Rep., Pres.}}_{c,2012-2016} + \boldsymbol{\Gamma} \boldsymbol{X}_{ic} + \varepsilon_{icd},$$

[14] 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 (e.g., Barberá et al. 2019). Furthermore, the House has the power to initiate impeachment, as with the Republican president at the initial time of writing.

where ν_{icd} is the vote share of the 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 (or Democratic) party, and W (or M) indicates a woman (or man) candidate, so that RW for instance, indicates a Republican woman candidate.

The main estimand of interest is β^{DW}. If there is indeed an advantage for the Democratic women candidates in counties with MeToo support, then $\beta^{DW} > 0$.[15] The full specification includes the interaction of the candidate party and gender with past electoral outcomes. $\boldsymbol{\nu}_{c,2016}^{\text{Rep., House}}$ is the full interaction of the 2016 house Republican vote share and candidate party; and $\boldsymbol{\nu}_{c,2012-2016}^{\text{Rep., Pres.}}$ 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.[16]

The vector $\boldsymbol{X}_{ic}$ are the county census demographics that enter as full interactions with party status. This prevents the DD estimates from capturing how votes differ by basic demographics (e.g., Edlund and Pande 2002; Herron and Sekhon 2005; Oswald and Powdthavee 2010). $\boldsymbol{X}_{ic}$ also includes the interaction of candidate ethnicity (African American, Hispanic, Others, and White) with the percentage composition of the corresponding ethnicity at the county level. 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 standard errors are clustered by candidates.[17]

[15] Both analytically and anecdotally, women from the Republican and Democratic parties are not expected to benefit equally, if at all, from the MeToo movement. The estimates show this analytically. Anecdotally, while half of Democratic non-incumbent women candidates express agreement and solidarity with the general zeitgeist of the 2018 movement, only one in five of Republican non-incumbent women candidates did so (Dittmar 2020). This is also bourne out in the estimates.

[16] Coefficients for third-party candidates not reported to conserve space.

[17] A well-known pattern during the midterms is a depression of the vote share for candidates who are from the same party as the sitting president. The party status dummies for candidates, nested within the candidate fixed effects, account for any potential swings so that the reported coefficients

4.2 Average Effects on Candidate Vote Share

Columns (1)–(2) of Table I reports the results from estimating Equation (1). All reported coefficients are in absolute terms so that the coefficients can be interpreted without requiring back-of-envelope differencing/addition.[18]

In column (1), only the DD estimates for candidate party gender and candidate fixed effects are included ($\Delta_1 = \Delta_2 = \Gamma = 0$ in Equation (1)), 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. Column (2) includes past electoral controls and county demographics as full interaction with the candidate party, together with a set of controls for ethnic and gender-based voting. Here, the estimated Democratic advantage and Republican disadvantage disappear.

The average effects in columns (1)–(2) of Table I, 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 MeToo-related backlash of Republican candidates in Republican strongholds.[19]

are interpreted as changes beyond the regular midterm swings.

[18] The full report of the three-way interaction between candidate party-gender, log tweet density, and the 2016 presidential Republican 2016 vote share is in Table A11.

[19] The F-tests for ethnic and gender voting are highly significant, suggesting a strong statistical tendency for voters to vote along their gender and party line, even if the overall variation it explains in candidate vote share is small. While not the focus of this study, voting by gender and ethnicity is in line with other findings in the literature (e.g., Abrajano and Alvarez 2005; Flanagan 2018; Holli and Wass 2010; Matsubayashi and Ueda 2011; Stephens-Davidowitz 2014).

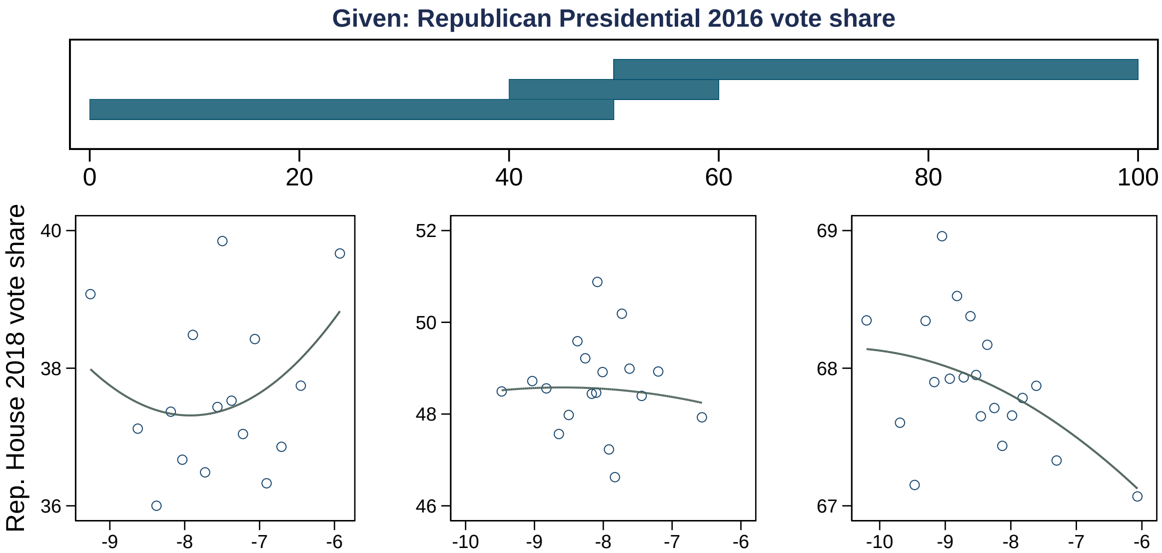

Figure VI: Conditional Effect of MeToo Movement[20]

4.3 Conditional Effect on Candidate Vote Share, by Existing Republican Support

The conditional plot in Figure VI provides visual indication of 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 a 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 absolute effects for ease of interpretation, is:

(2)

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

[20] Horizontal axis is the log of MeToo tweets. Binned scatter plots are with past electoral trends already partialed out.

where the main coefficients of interest are the γ^j's.

The main estimand of interest is γ^{DW}. $\gamma^{DW} > 0$ 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 (2) 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 I 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.

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 splits (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 ($p < 0.01$) relative to their peers in counties with a 50–50 split in the Republican vote share.[21] [22]

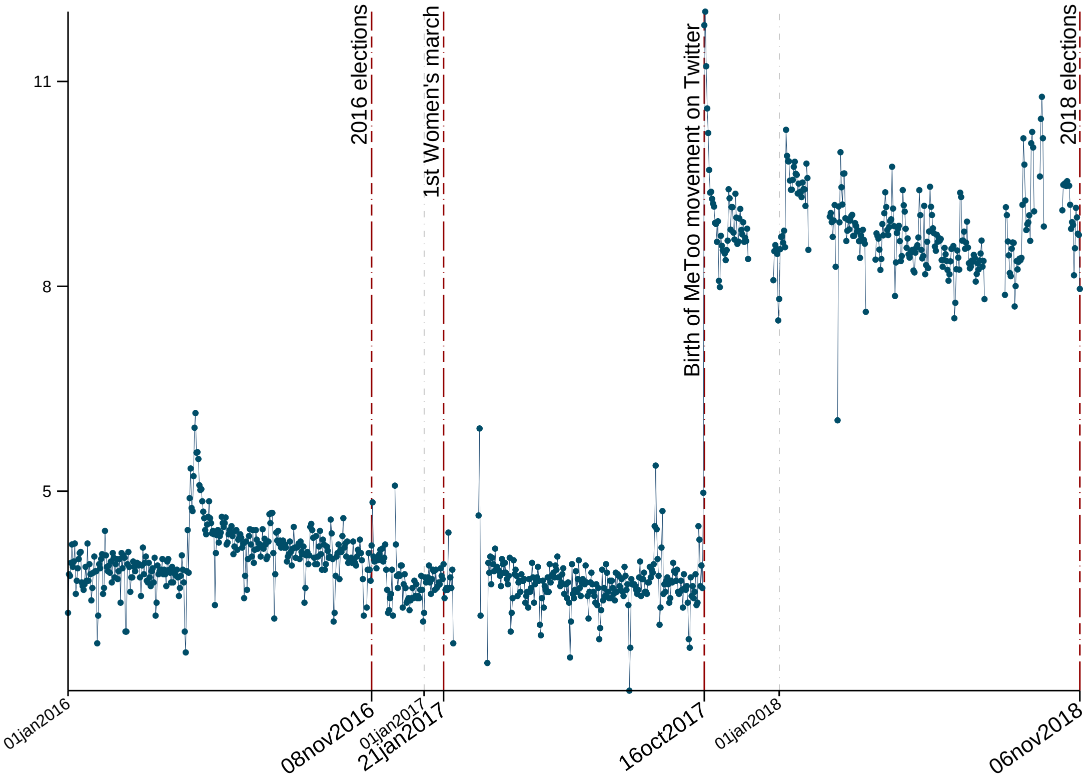

Figure VII: EXTENDED TIMELINE OF METOO TWEETS

4.4 Back to the 2016 House Elections

The above result does not negate a temporal trend (as in Lilley and Wheaton 2019). To test if the results from Table I are capturing existing trends, I use another set of data on individual candidate vote share from the 2016 House elections. Since I am using the level of MeToo support captured in 2018, the observed effect of the MeToo movement in the 2018 House elections should not be present in the 2016 House elections.

Table II reports the result and uses the same regression specification aside from the temporal switch to 2016 in the dependent variable. The estimates from Table II are similar to the baseline in Table I. Areas, where Democratic candidates in the 2018 House elections appear to benefit from the grassroots MeToo movement, are also areas where Democratic candidates have an advantage in the 2016 House

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

[22] Column (5) uses district fixed effects instead of candidate fixed effects. 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.

elections before the MeToo movement reached its peak (see Figure VII). This effect may be attributable to underlying shifts in demographics. I discuss this in more detail in Appendix A.5. There is hence limited causal evidence that Democratic women candidates benefited passively from MeToo pressure at the county level. In the following section, I explore strategic candidacy and turnout to help shed light on how political agents actively exploit the movement.

5 Strategic Candidacy and Turnout

5.1 Candidacy as Strategic Reaction

One potential channel through which the MeToo movement works is by increasing the likelihood that non-traditional political candidates who fit the MeToo zeitgeist stand for elections. The Appendix A.4 tests and shows that the measure of log tweet density does not predict the selection of women candidates at the district level, condition on the past election returns, demographics, and the state fixed effects. Given the subtle results above, a more authentic test is to examine whether the MeToo tweets affected candidacy only in particular classes of political seats.

Specifically, I augment the tests from Equation (A2) and Table A6 and test whether the probability of having a Democratic woman challenger in: (i) districts with Republican incumbents and (ii) districts with Democratic man incumbents, is moderated by the MeToo measure (Hainmueller et al. 2019). Figure VIII reports the marginal effects over the range of the MeToo measure, controlling for electoral trends, demographics, and the state fixed effects. The solid black lines inside the 95% confidence intervals (constructed from standard errors clustered by states) report the marginal effects at different levels of the MeToo tweets measure, and the stacked histograms indicate the distribution of house seats for the particular class of interest. As expected, the confidence intervals are increasingly wide at log tweet density levels with fewer observations.

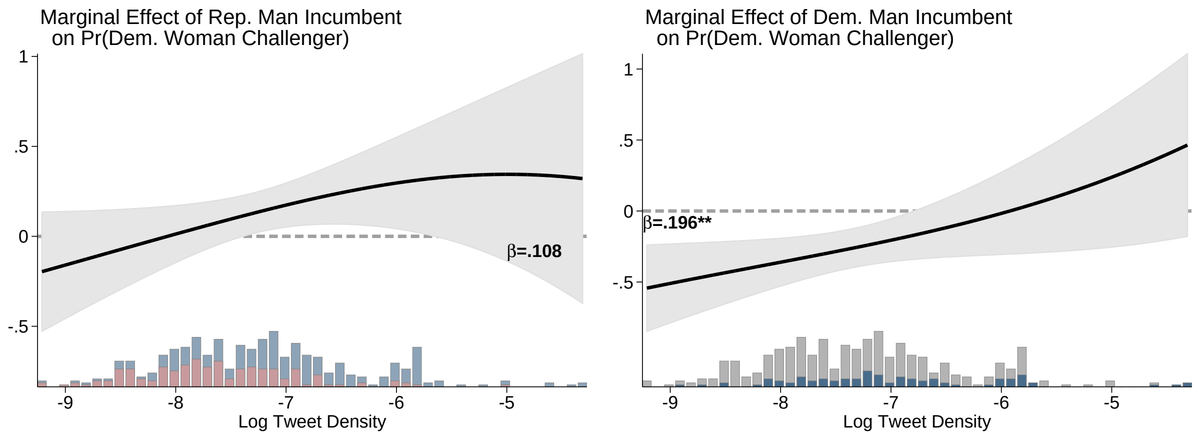

Figure VIII: Candidacy as Strategic Reaction

As consistent with the story that candidacy was a strategic reaction to the MeToo movement, the marginal effect, while non-linear, increases with the MeToo tweets in Figure VIII. In the left panel of Figure VIII, the single coefficient estimate is insignificant. However, the kernel estimates (Hainmueller et al. 2019) suggest that the effect is positive and significant at moderately high levels of the MeToo movement support. With higher MeToo support in districts with a Republican man incumbent, the probability of a Democratic woman challenger is more likely. This effect is most precisely estimated at moderate levels of the MeToo support.

In the right panel of Figure VIII, what may perhaps be more surprising is that a similar effect exists, but for districts where the incumbent is a Democratic man. When a district has an incumbent from the Democratic Party, its effect on the probability of having a women candidate from the same party is negative, as expected. This could be because of within-party norms such that same-party contests of the incumbent and multiple same-party contests are rare. This negative effect, however, starts reversing in districts with high MeToo movement. In districts with high MeToo tweets, the likelihood of a woman vs. a man candidate from the Democratic party becomes closer to a coin toss.

Overall, the results from Figure VIII suggest that a key political economy mechanism is through candidate selection, where opportunistic political actors catch the winds of change in the MeToo movement. Woman candidates from the Democratic

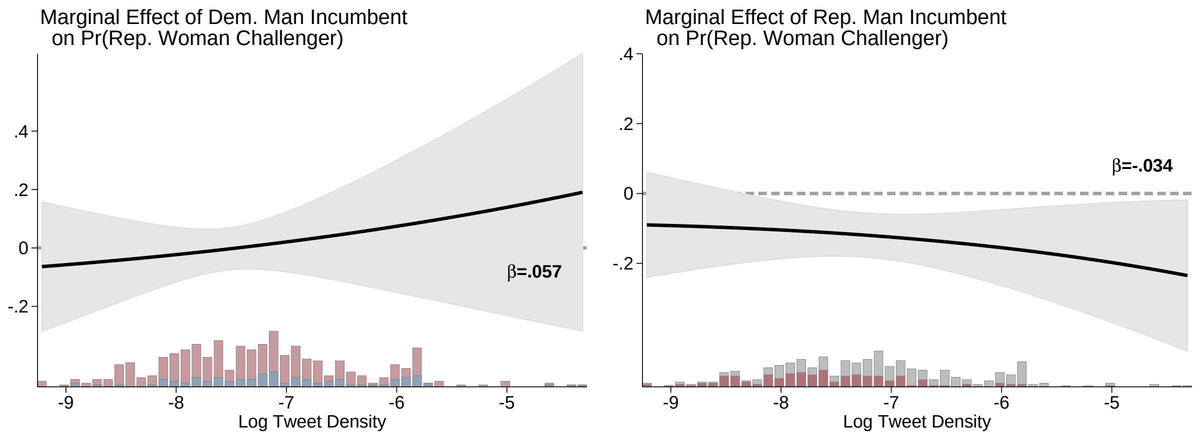

Figure IX: Candidacy as Strategic Reaction (Republican Women Challengers)

Party are more likely to stand in districts with a Republican incumbent and also in districts where the seat is held by a Democratic man, where support for the MeToo movement is high.

To be clear, this effect is not present for Republican woman challengers when the parties are reversed in the specification (Figure IX). It appears the movement shifted incentives in candidacy, where women, traditionally considered more outsider and less centrist in the established Democratic party machinery, are more likely to be frontrunners.

Going back to the records of the congressional district returns, I identify six successful Democratic non-incumbent women in districts where the incumbent was a co-partisan man. One of these is from a vacant seat, where the incumbent stepped down a year prior because of accusations of sexual misconduct (as noted in Carlsen et al. 2018). Four of them, including the one above, are part of the left-leaning Democratic group known as “The Squad”. All of them succeeded in districts that are pronouncedly Democratic, as evident in the Cook Partisan Voting Index (CPVI) with a score of more than D+25. The remaining two Democratic non-incumbent women candidates who successfully won a seat against their male co-partisans are in Texas, in districts that are also safe Democratic areas with a CPVI of D+17 and D+19. In this sense, one would be hard press to think that this group of non-incumbent candidates drove the overall Democratic gains in the 2018 elections.

Looking at the Democratic non-incumbent women candidates who supplanted Republican men tells a different story. I identify 17 such districts. Based on the CPVI, most of these districts lean Republican. Among the 17 districts where Democratic non-incumbent women supplanted Republican men, the Oklahoma 5 district is the most Republican out of the 17 districts based on the CPVI of R+10. The Democratic challenger Kendra Horn's win in this district thus constitutes one of the biggest political upsets in 2018. She subsequently lost her seat in the 2020 elections to Republican candidate Stephanie Bice. Lizzie Fletcher, on the other hand, won the Texas 7 district (second highest CPVI towards Republican of R+7 in the 17 districts) in 2018 against Republican John Culberson and won her reelection in 2020 against the Republican candidate Wesley Hunt. Both cases fit into the narrative of a demand for more women in political offices, conditional on the aggregate partisanship of the area.

Overall, the wave of women candidates in the 17 districts appears to be the ones contributing most to the Democratic gain in the 2018 house elections. Moreover, to the extent that these districts also have high recorded MeToo support based on the geolocated tweets, this appears to be the primary channel through which the MeToo movement is linked to the historic performance of women candidates in the 2018 house elections. The fact that the non-incumbent women candidates in 2018 are no different than their predecessors (Thomsen and King 2020) and that more women are contesting (Center for American Women and Politics 2018) supports this interpretation.

5.2 Turnout

The 2018 midterm elections set a record high in turnout (Center for American Women and Politics 2018). A natural question is whether the MeToo movement had a part to play in turning out voters. To test this, I estimate the model:

$$(3) \qquad t_c^{\text{House 2018}} - t_c^{\text{House 2016}} = \alpha + \beta_1 \tau_c + \beta_2 \nu_{c,\ 2016}^{\text{Rep., Pres.}} + \gamma(\tau \cdot \nu^{\text{Rep., Pres.}})_c + \boldsymbol{\Gamma X}_c + \varepsilon_c,$$

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 demographic controls now include both levels and trends (using the ACS 5-year estimates from 2012–16 and 2015–19), including the percentage of citizen voting-age population.

Table III presents the results, which is consistent with the heterogeneous effect in Table I. First, columns (1)–(2) show that the log tweet density measure does not predict a change in turnout. In columns (3)–(4), I replace the tweets measure with the log tweet *intensity* measure (without dividing by county population), and the interaction term (γ in Equation (3)) is now positive. The estimate in column (4) implies that for a standard deviation increase in log tweets intensity (1.946), every ten percentage point increase in the Republican vote share increases turnout by 1.17% ($p < 0.05$).

As a falsification test, I repeat the regressions in Table III, 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 IV). Figure VII shows that the MeToo movement on Twitter begins in full force only from 16 October 2017.[23]

The results from Table III 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 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

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

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.[24]

6 Discussion and Conclusion

In 2018, what was once privately experienced harrowing episodes catalyzed into the public sphere through the #MeToo movement on Twitter and other social media platforms (Goenaga 2022). This grassroots-driven social media activity formed the bedrock of the 2018 zeitgeist and led to suggestions that change in legislation to protect women, potentially through better women representation in Congress, is imminent (e.g., Deckman 2018; Peaker 2018; Tippett 2018a; Thomsen and King 2020).[25]

This article investigates whether the movement had a role in the historical 2018 house elections, where Congress saw the highest number of successful women challengers. This study finds an advantage for Democratic women candidates in the 2018 House elections in Republican counties with high support for the MeToo movement. Unfortunately, this correlation can also be found in the 2016 House elections, two years before the MeToo reached its peak in 2018, disputing causal claims that candidates benefited passively.

Instead, this study adduces evidence that turnout is higher in Republican counties with high MeToo support, something not found in the 2016 elections. Moreover, there is evidence of a candidacy strategy where Democratic women candidates are

[24] If turnout is a channel, then counties with more turnout should see more shift in vote shares to the Democratic party in Republican counties with high MeToo pressure. The Appendix A.6 documents some evidence of this.

[24] The MeToo movement blew up on Twitter on 16 October 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 in the figure. Figure A3 plots the timeline in level terms.

[25] At the time of initial 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.

more likely to challenge Republican man incumbents in districts with high MeToo support. These results point to how political agents were cognizant of the grassroots movement and actively campaigned in tandem with the MeToo to gain political advantages.

Potential avenues of research include whether the MeToo effect persists into the next round of elections, which include the Republican president, a subject of the movement himself. In terms of minority representation, one may be interested in whether the 2018 congressional composition substantially changed public goods provision (as in Chattopadhyay and Duflo 2004; Pande 2003). Given how state judges were recalled for being lenient in sexual assault cases, another potential study relating to legal realism is on whether the movement induces harsher sentencing in sexual assault crimes.

References

Abrajano, Marisa A, and R Michael Alvarez. 2005. "A Natural Experiment of Race-Based and Issue Voting: The 2001 City of Los Angeles Elections." *Political Research Quarterly* 58 (2): 203–218. 10.1177/106591290505800202.

Acemoglu, Daron, Tarek A. Hassan, and Ahmed Tahoun. 2018. "The power of the street: Evidence from Egypt's arab spring." *Review of Financial Studies* 31 (1): 1–42. 10.1093/rfs/hhx086.

Adena, Maja, Ruben Enikolopov, Maria Petrova, Veronica Santarosa, and Ekaterina Zhuravskaya. 2015. "Radio and the Rise of The Nazis in Prewar Germany." *The Quarterly Journal of Economics* 130 (4): 1885–1939. 10.1093/qje/qjv030.

Ban, Pamela, Justin Grimmer, Jaclyn Kaslovsky, and Emily West. 2022. "How Does the Rising Number of Women in the U.S. Congress Change Deliberation? Evidence from House Committee Hearings." *Quarterly Journal of Political Science* 17 (3): 355–387. 10.1561/100.00020112.

Barberá, Pablo, Andreu Casas, Jonathan Nagler, Patrick J Egan, Richard Bonneau, John T Jost, and Joshua A Tucker. 2019. "Who Leads? Who Follows? Measuring Issue Attention and Agenda Setting by Legislators and the Mass Public Using Social Media Data." *American Political Science Review* 113 (4): 883–901. DOI:10.1017/S0003055419000352.

Boas, Taylor C, and F Daniel Hidalgo. 2011. "Controlling the Airwaves: Incumbency Advantage and Community Radio in Brazil." *American Journal of Political Science* 55 (4): 869–885. 10.1111/j.1540-5907.2011.00532.x.

Campante, Filipe, Ruben Durante, and Francesco Sobbrio. 2017. "Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation." *Journal of the European Economic Association* 16 (4): 1094–1136. 10.1093/jeea/jvx044.

Carlsen, Audrey, Maya Salam, Claire Cain Miller, Denise Lu, Ash Ngu, Jugal K. Patel, and Zach Wichter. 2018. "#MeToo Brought Down 201 Powerful Men. Nearly Half of Their Replacements Are Women." *The New York Times*, `https://www.nytimes.com/interactive/2018/10/23/us/metoo-replacements.html`.

Center for American Women and Politics. 2018. "Women Candidates for Congress 1974-2018."Technical report, `http://www.cawp.rutgers.edu/sites/default/files/resources/canwincong_histsum.pdf`.

Chattopadhyay, Raghabendra, and Esther Duflo. 2004. "Women as Policy Makers: Evidence from a Randomized Policy Experiment in India." *Econometrica* 72 (5): 1409–1443. 10.1111/j.1468-0262.2004.00539.x.

Coppock, Alexander, and Donald P Green. 2016. "Is Voting Habit Forming? New Evidence from Experiments and Regression Discontinuities." *American Journal of Political Science* 60 (4): 1044–1062. https://doi.org/10.1111/ajps.12210.

Deckman, Melissa. 2018. "#MeToo and the Midterms." *Gender Watch 2018*, `http://www.genderwatch2018.org/metoo-and-the-midterms/`.

DellaVigna, Stefano, and Ethan Kaplan. 2007. "The Fox News Effect: Media Bias and Voting." *Quarterly Journal of Economics* 122 (3): 1187–1234. 10.1162/qjec.122.3.1187.

Democracy Fund Voter Study Group. 2018. "Views of the Electorate Research Survey." `https://www.voterstudygroup.org/`.

Dittmar, Kelly. 2020. "Urgency and ambition: the influence of political environment and emotion in spurring US women's candidacies in 2018." *European Journal of Politics and Gender* 3 (1): 143–160. 10.1332/251510819X15728693158427.

Edlund, Lena, and Rohini Pande. 2002. "Why Have Women Become Left-Wing? The Political Gender Gap and the Decline in Marriage." *The Quarterly Journal of Economics* 117 (3): 917–961. 10.1162/003355302760193922.

Eisele, Olga, Elena Escalante-Block, Alena Kluknavská, and Hajo G Boomgaarden. 2022. "The politicising spark? Exploring the impact of #MeToo on the gender equality discourse in Australian print media." *Australian Journal of Political Science* 1–19. 10.1080/10361146.2022.2045900.

Enikolopov, Ruben, Maria Petrova, and Ekaterina Zhuravskaya. 2011. "Media and Political Persuasion: Evidence from Russia." *American Economic Review* 101 (7): 3253–3285. 10.1257/aer.101.7.3253.

Feinberg, Ayal, Regina Branton, and Valerie Martinez-Ebers. 2019. "The Trump Effect: How 2016 Campaign Rallies Explain Spikes in Hate."

Ferraz, Claudio, and Frederico Finan. 2008. "Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes." *The Quarterly Journal of Economics* 123 (2): 703–745. 10.1162/qjec.2008.123.2.703.

Fischer, A J. 1996. "A further experimental study of expressive voting." *Public Choice* 88 (1): 171–184. 10.1007/BF00130417.

Flanagan, Francis X. 2018. "Race, Gender, and Juries: Evidence from North Carolina." *The Journal of Law and Economics* 61 (2): 189–214. 10.1086/698193.

Fowler, James H. 2006. "Habitual Voting and Behavioral Turnout." *The Journal of Politics* 68 (2): 335–344. 10.1111/j.1468-2508.2006.00410.x.

Fujiwara, Thomas, Karsten Müller, and Carlo Schwarz. 2020. "The Effect of Social Media on Elections: Evidence from the United States." *SSRN Electronic Journal*. 10.2139/ssrn.3719998.

Gentzkow, Matthew. 2006. "Television and Voter Turnout." *The Quarterly Journal of Economics* (3): 931. 10.1162/qjec.121.3.931.

Gentzkow, Matthew, and Jesse M Shapiro. 2010. "What Drives Media Slant? Evidence From U.S. Daily Newspapers." *Econometrica* 78 (1): 35–71. 10.3982/ECTA7195.

Gibson, Camille, Shannon Davenport, Tina Fowler, Colette B Harris, Melanie Prudhomme, Serita Whiting, and Sherri Simmons-Horton. 2019. "Understanding the 2017 "Me Too" Movement's Timing." *Humanity and Society* 43 (2): 217–224. 10.1177/0160597619832047.

Goenaga, Agustin. 2022. "Who cares about the public sphere?." *European Journal of Political Research* 61 (1): 230–254. https://doi.org/10.1111/1475-6765.12451.

Groseclose, Tim, and Jeffrey Milyo. 2005. "A Measure of Media Bias." *Quarterly Journal of Economics* 120 (4): 1191–1237. 10.1162/003355305775097542.

Hainmueller, Jens, Jonathan Mummolo, and Yiqing Xu. 2019. "How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice." *Political Analysis* 27 (2): 163–192. DOI: 10.1017/pan.2018.46.

Herron, Michael C, and Jasjeet S Sekhon. 2005. "Black Candidates and Black Voters: Assessing the Impact of Candidate Race on Uncounted Vote Rates." *The Journal of Politics* 67 (1): 154–177. 10.1111/j.1468-2508.2005.00312.x.

Hillman, Arye L. 2010. "Expressive behavior in economics and politics." *European Journal of Political Economy* 26 (4): 403–418. https://doi.org/10.1016/j.ejpoleco.2010.06.004.

Holli, Anne Maria, and Hanna Wass. 2010. "Gender-based voting in the parliamentary elections of 2007 in Finland." *European Journal of Political Research* 49 (5): 598–630. 10.1111/j.1475-6765.2009.01910.x.

Kim, Taegyoon. 2022. "Violent political rhetoric on Twitter." *Political Science Research and Methods* 1–23. DOI:10.1017/psrm.2022.12.

Larcinese, Valentino, Riccardo Puglisi, and James M Snyder. 2011. "Partisan Bias in Economic News: Evidence on the Agenda-setting Behavior of U.S. Newspapers." *Journal of Public Economics* 95 (9): 1178–1189. 10.1016/j.jpubeco.2011.04.006.

Larreboure, Magdalena, and Felipe Gonzalez. 2021. "The Impact of the Women' s March on the U.S. House Election."

Larreguy, Horacio A, John Marshall, and James M Snyder Jr.. 2014. "Revealing Malfeasance: How Local Media Facilitates Electoral Sanctioning of Mayors in Mexico." *National Bureau of Economic Research Working Paper Series* No. 20697 1–57. 10.3386/w20697.

Leon-Ablan, Gabriel, and Peter John. 2022. "How urban riots influence political behavior: vote choices after the 2011 London riots." *Political Science Research and Methods* 1–8. DOI:10.1017/psrm.2022.49.

Lilley, Matthew, and Brian Wheaton. 2019. "Trump Rallies and Hate Crimes: A Comment on Feinberg et al. (2019)."

Lim, Claire S H, James M Snyder, and David Strömberg. 2015. "The Judge, the Politician, and the Press: Newspaper Coverage and Criminal Sentencing across Electoral Systems." *American Economic Journal: Applied Economics* 7 (4): 103–135. 10.1257/app.20140111.

Matsubayashi, Tetsuya, and Michiko Ueda. 2011. "Political Knowledge and the Use of Candidate Race as a Voting Cue." *American Politics Research* 39 (2): 380–413. 10.1177/1532673X10363977.

Miner, Luke. 2015. "The Unintended Consequences of Internet Diffusion: Evidence from Malaysia." *Journal of Public Economics* 132 66–78. 10.1016/j.jpubeco.2015.10.002.

MIT Election Data and Science Lab. 2018a. "County Presidential Election Returns 2000-2016." doi:10.7910/DVN/VOQCHQ.

MIT Election Data and Science Lab. 2018b. "U.S. House of Representatives Precinct-Level Returns 2016." doi:10.7910/DVN/PSKDUJ.

Munger, Kevin, Richard Bonneau, Jonathan Nagler, and Joshua A Tucker. 2019. "Elites Tweet to Get Feet Off the Streets: Measuring Regime Social Media Strategies During Protest." *Political Science Research and Methods* 7 (4): 815–834. DOI:10.1017/psrm.2018.3.

North, Anna. 2019. "Democrats' sweeping new anti-harassment bill, explained." `https://www.vox.com/2019/4/9/18300478/sexual-harassment-me-too-be-heard-democrats`.

Oberholzer-Gee, Felix, and Joel Waldfogel. 2009. "Media Markets and Localism: Does Local News en Español Boost Hispanic Voter Turnout?." *American Economic Review* 99 (5): 2120–2128. 10.1257/aer.99.5.2120.

Oswald, Andrew J, and Nattavudh Powdthavee. 2010. "Daughters and Left-Wing Voting." *The Review of Economics and Statistics* 92 (2): 213–227. 10.1162/rest.2010.11436.

Pande, Rohini. 2003. "Can Mandated Political Representation Increase Policy Influence for Disadvantaged Minorities? Theory and Evidence from India." *American Economic Review* 93 (4): 1132–1151. 10.1257/000282803769206232.

Peaker, Hannah. 2018. "This was a #Metoo election and those who say differently ignore the 'Pink Wave' at their peril." *The Telegraph*, `https://www.telegraph.co.uk/women/politics/metoo-election-say-differently-ignore-pink-wave-peril/`.

Rajan, Amol. 2019. “Twitter to ban all political advertising.” *BBC*, https://www.bbc.com/news/world-us-canada-50243306.

Singer, Jordan M. 2019. “Judicial Recall and Retention in the #MeToo Era.” *Court Review* 55 (1): 36–43, https://heinonline.org/HOL/P?h=hein.journals/ctrev55&i=36https://heinonline.org/HOL/PrintRequest?handle=hein.journals/ctrev55&collection=journals&div=10&id=36&print=section&sction=10.

Sobolev, Anton, M Keith Chen, Jungseock Joo, and Zachary C Steinert-Threlkeld. 2020. “News and Geolocated Social Media Accurately Measure Protest Size Variation.” *American Political Science Review* 114 (4): 1343–1351. DOI:10.1017/S0003055420000295.

Stephens-Davidowitz, Seth. 2014. “The cost of racial animus on a black candidate: Evidence using Google search data.” *Journal of Public Economics* 118 26–40. https://doi.org/10.1016/j.jpubeco.2014.04.010.

Thomsen, Danielle M, and Aaron S King. 2020. “Women’s Representation and the Gendered Pipeline to Power.” *American Political Science Review* 114 (4): 989–1000. DOI:10.1017/S0003055420000404.

Tippett, Elizabeth C. 2018a. “How the ’wave of women’ entering Congress could turn the #MeToo movement into concrete action.” *Business Insider*, https://www.businessinsider.com/women-entering-congress-could-turn-the-metoo-movement-into-action-2018-11.

Tippett, Elizabeth C. 2018b. “The Legal Implications of the MeToo Movement.” *Minnesota Law Review* 103 (1): 229–302, https://heinonline.org/HOL/P?h=hein.journals/mnlr103&i=239https://heinonline.org/HOL/PrintRequest?handle=hein.journals/mnlr103&collection=journals&div=15&id=239&print=section&sction=15.

Tyran, Jean-Robert. 2004. “Voting when money and morals conflict: an experimental test of expressive voting.” *Journal of Public Economics* 88 (7): 1645–1664. https://doi.org/10.1016/S0047-2727(03)00016-1.

Walsh, John. 2018. “‘Kavanaugh’s Revenge’: Every Democratic senator in a competitive midterm race who voted against Brett Kavanaugh lost.” https://www.businessinsider.sg/democratic-senators-who-voted-against-brett-kavanaugh-lost-close-reelection-races-2018-11/?r=US&IR=T.

Weiss, Chagai M, Alexandra A. Siegel, and David Romney. 2022. “How Threats of Exclusion Mobilize Palestinian Political Participation.” *American Journal of Political Science* n/a (n/a): . https://doi.org/10.1111/ajps.12718.

Ye, Junting, Shuchu Han, Yifan Hu, Baris Coskun, Meizhu Liu, Hong Qin, and Steven Skiena. 2017. “Nationality Classification using Name Embeddings.” *CIKM*. 10.1145/nnnnnnn.nnnnnnn.

7 Tables

Table I
The Effect of the MeToo Movement on Candidate Vote Share

			Heterogeneous effect, by presidential Republicanvote share in 2016		
	All-party vote share			Two-party vote share	
	(1)	(2)	(3)	(4)	(5)
Log tweet density × (Rep. woman)	-3.557^{***}	-0.674	-0.707	-0.472	-0.193
	(0.993)	(0.574)	(0.724)	(0.713)	(0.699)
Log tweet density × (Dem. woman)	2.073^{***}	0.074	-0.655^{***}	-0.930^{***}	-0.636^{**}
	(0.492)	(0.188)	(0.253)	(0.287)	(0.312)
Log tweet density × (Rep. man)	-2.218^{***}	0.008	0.300	0.408	0.302
	(0.410)	(0.157)	(0.235)	(0.255)	(0.272)
Log tweet density × (Dem. man)	2.316^{***}	0.279	-0.029	-0.439	-0.592
	(0.515)	(0.232)	(0.354)	(0.431)	(0.436)
Log tweet density × (Pres. 2016 Rep. vote share) × (Rep. woman)			-0.023	-0.027	-0.027
			(0.030)	(0.029)	(0.028)
Log tweet density × (Pres. 2016 Rep. vote share) × (Dem. woman)			0.037^{***}	0.047^{***}	0.043^{***}
			(0.014)	(0.013)	(0.015)
Log tweet density × (Pres. 2016 Rep. vote share) × (Rep. man)			-0.021^{**}	-0.022^{**}	-0.024^{**}
			(0.009)	(0.009)	(0.010)
Log tweet density × (Pres. 2016 Rep. vote share) × (Dem. man)			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 II

THE HETEROGENEOUS 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 Republicanvote share. All controls are otherwise the same as in Table I. 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 III

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	0.0221	−0.0162	0.0145	−0.0221
	(0.0144)	(0.0347)	(0.0121)	(0.0180)
Pres. 2016 Rep. vote share	−0.0128***	−0.0081*	−0.0127***	−0.0136***
	(0.0025)	(0.0046)	(0.0025)	(0.0025)
$\tau \times$ (Pres. 2016 Rep. vote share)		0.0006		0.0006***
		(0.0004)		(0.0002)
District fixed effects	X	X	X	X
Census Control	X	X	X	X
F-test: Electoral controls = 0	$F = 19.19$***	$F = 4.32$***	$F = 19.26$***	$F = 18.1$***
F-test: County census = 0	$F = 2.72$***	$F = 2.74$***	$F = 2.47$***	$F = 2.53$***
R^2	0.6551	0.6557	0.6543	0.6556
N	3102	3102	3102	3102

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 include the 14 demographic variables and additionally the percentage of citizen voting-age population; these are entered as both levels and changes from the ACS 5-year estimates for 2012–16 and the ACS 5-year estimates for 2015–19, except for the percentage rural population available only from the decennial census. 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 IV

The Effect of the MeToo Movement on Turnout (Falsification—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	−0.0022	0.0012	0.0030
	(0.0008)	(0.0034)	(0.0008)	(0.0021)
Pres. 2016 Rep. vote share		−0.0019***		−0.0021***
		(0.0007)		(0.0007)
$\tau \times$ (Pres. 2016 Rep. vote share)		0.0000		−0.0000
		(0.0001)		(0.0000)
District fixed effects	X	X	X	X
Census Control	X	X	X	X
F-test: County census = 0	$F = 30.01$***	$F = 24.12$***	$F = 27.66$***	$F = 25.26$***
R^2	0.6985	0.7025	0.6988	0.7028
N	3158	3158	3158	3158

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 include the 14 demographic variables and additionally the percentage of citizen voting-age population; these are entered as both levels and changes from the ACS 5-year estimates for 2012–16 and the ACS 5-year estimates for 2015–19, except for the percentage rural population available only from the decennial census. 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.

A Appendix

A.1 Data Appendix

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-US country                          */
        if len(geoloc)==2 then
            check if geoloc matches a non-US country using ISO alpha-2 code
        else if len(geoloc)==3 then
            check if geoloc matches a non-US country using ISO alpha-3 code
        else
            check if geoloc matches a non-US country using ISO country name name
        if not unambiguously non-US country in [Step 1] then
            /* [Step 2] Try geoloc string as US 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 US city (e.g. 'chicago' as Chicago City in Illinois)
        if still not identified as a US city-state in [Step 2] then
            /* [Step 3] Try geoloc string as US 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-US country                          */
        check if one side of comma is unambiguously a non-US country as in [Step 1] (e.g., 'beunos aires,
          argentina' should be filtered out)
        if not unambiguously a non-US country then
            /* [Step 5] Try as a US 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 US 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 US 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 US 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.

Table A2
SUMMARY STATISTICS

	Obs.	Min	Max	Mean	Std. Dev.
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.

A.2 Validating Geolocated MeToo Tweets

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? Astroturfing generally refers to the practice of coordinated but inauthentic political activity masquerading as true grassroots activity. Notably, astroturfing is easy/cheap to directly implement on online platforms, including social media. While definitive evidence is difficult, arguments can be made against it.

First, the correlation between the MeToo tweet measures and county demographics provides 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 A1). This does not square with a broad-based generation of fake grassroots.

Second, Figure I reports the timeline of the 2018 MeToo tweets for both the global MeToo tweets and those that are successfully matched to U.S. counties. I make two observations here. The 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 US counties—some, because they are unambiguously outside the US —the plot, shows that the time trend of the global tweets and the identifiable US counties tweets are similar, suggesting that there is no systematic difference in the tweets that can and cannot be matched to US counties. This supports the assumption that the tweets are capturing grassroots sentiments (Figure I and note 5).

A check against astroturfing is to cut off aggregation of the 2018 tweets measure before June when most primary elections occur.[1] 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 A7 shows that the results are not substantially different when using only pre-primary (pre-June) tweets and when dropping districts with low within-district variation in the tweets measure.

[1] 17 states have their primaries in June. See http://www.ncsl.org/research/elections-and-campaigns/2018-state-primary-election-dates.aspx.

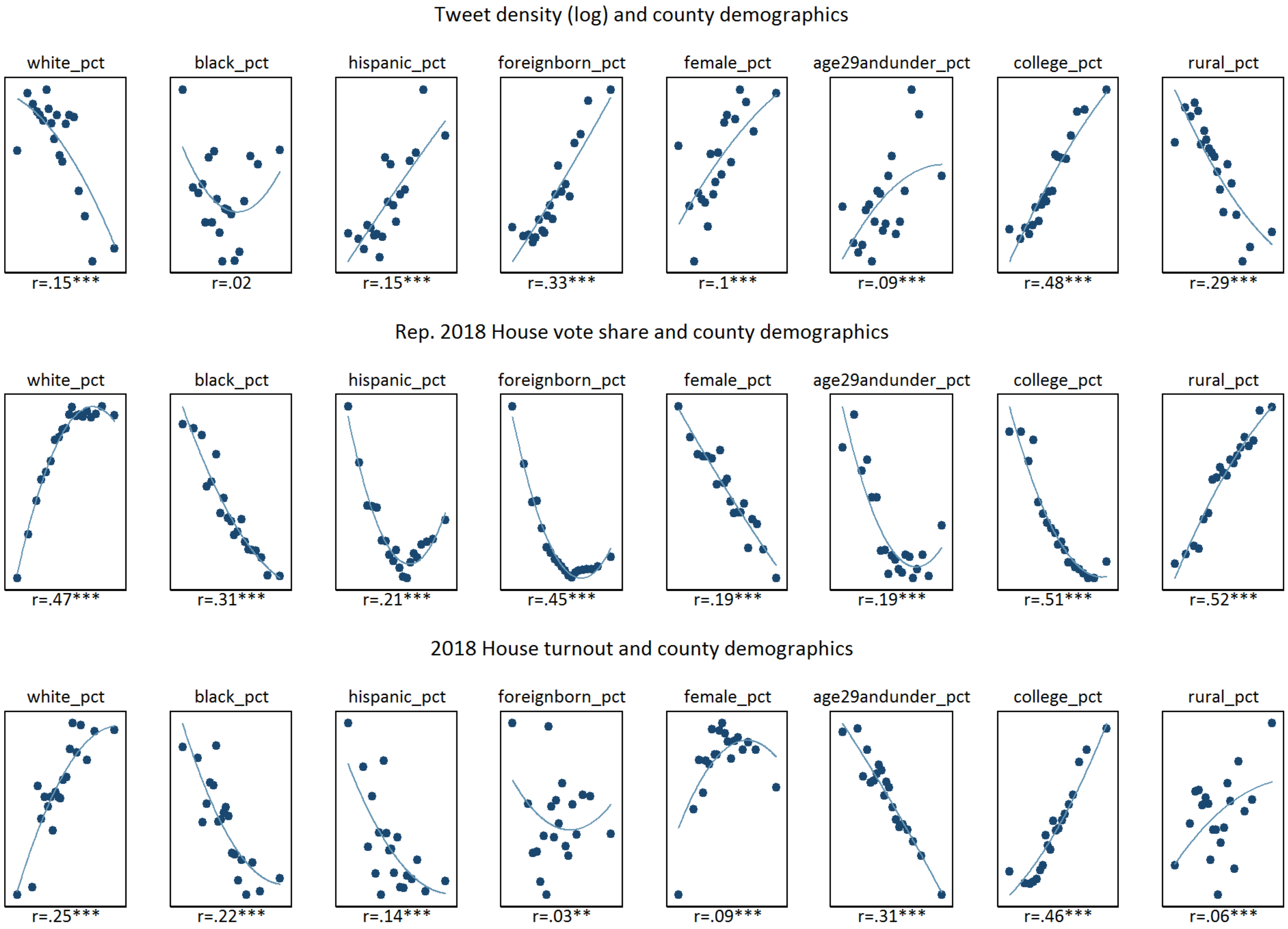

Figure A1: Correlation (Binned Scatters) between County Demographics, Tweets, and 2018 House Elections

Table A3

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)	$\mathbb{1}$(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)
$\mathbb{1}$(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)
$\mathbb{1}$(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.

***VOTER* (Views of the Electorate Research) survey (Democracy Fund Voter Study Group 2018)** To check that the geolocated MeToo tweets at the county-level 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. Change variables are computed for individuals that have been tracked throughout.

Table A3 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. The set of individual characteristics include gender, race, education, employment, birth cohort (by decade), income, marital status, and the 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.

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 sexism. 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). 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 col-

Table A4

THE EFFECT OF METOO ON INDIVIDUAL VOTING (VOTER DATA)

	𝟙(Voted Republican) in 2016	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)
𝟙(Always vote for Democrats)	-0.077^{***}	-0.077^{***}	0.003
	(0.012)	(0.012)	(0.011)
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.

umn (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 A3 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.

Table A4 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 A3. Further, the tweet density measure also increases the probability that the individual switch their vote to the Democratic party from 2016 to 2018. These findings are consistent with how geolocated Twitter data are valid indicators of protest movements (e.g. Sobolev et al. 2020).

Table A5
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.

A.3 Determinants of Tweets

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

$$\text{(A1)} \qquad \tau_c = \alpha + \boldsymbol{\beta}_1 \boldsymbol{\nu}^{\text{Rep., House}}_{c,\ 2016} + \boldsymbol{\beta}_2 \boldsymbol{\nu}^{\text{Rep., Pres.}}_{c,\ 2012-16} + \boldsymbol{\Gamma} \boldsymbol{X}_c + \varepsilon_c,$$

where the dependent variable τ_c is the log of the county-level MeToo tweet density—the number of (identified) county-level MeToo tweets in 2018 (before the elections) divided by county population. $\boldsymbol{\nu}^{\text{Rep., House}}_{c,\ 2016}$ are the 2016 house Republican vote share and turnout, $\boldsymbol{\nu}^{\text{Rep., Pres.}}_{c,\ 2012-16}$ are the 2012–16 change in vote share and change in turnout, and $\boldsymbol{X}_c$ are the county census variables (described in Section 2). Standard errors are clustered at the congressional districts.

Table A5 reports the results. Overall, once the congressional house district fixed effects are added, the county-level MeToo tweets density and past election returns are no longer correlated.

Column (1) of Table A5 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.

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 ($p < 0.05$). 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.

A.4 Women Candidates in Districts

In Table A6, I check what covariates are linked to the presence of women candidates for the 388 US congressional districts in the sample. The MeToo tweets density and past electoral returns are not correlated with indicators for the presence of women candidates at the district level. Specifically, the model I estimate is:

$$I_{ds} = \alpha + \beta\tau_d + \mathbf{\Gamma}\boldsymbol{X}_d + \mathbf{\Delta}\boldsymbol{Z}_d + \text{state}_s + \varepsilon_{ds}, \tag{A2}$$

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

Table A6

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.

trends. All regressions include state fixed effects, with standard errors clustered at the 44 states in the sample.

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 ($p < 0.01$). I explore this channel in detail in Section 5.1.

A.5 Additional Results and Discussion on Candidate Vote Share

Potential Sources of Bias In what scenarios would the DD estimates be biased? An important identifying assumption in the DD specification (1) is that candidate campaigning across counties of a district is uniform. And, if there are heterogeneities in campaigning across counties, 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 A6, however, that the tweets are orthogonal to 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 behavior unlikely. In an additional robustness check in Table A8, 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.

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 tweet measure is

Table A7
Robustness

	Robustness check for Column (4) of Table I						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log tweet density × (Pres. 2016 Rep. vote share) × (Rep. woman)	−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)
Log tweet density × (Pres. 2016 Rep. vote share) × (Dem. woman)	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)
Log tweet density × (Pres. 2016 Rep. vote share) × (Rep. man)	−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)
Log tweet density × (Pres. 2016 Rep. vote share) × (Dem. man)	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 MeTootweets	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 I. 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 A8

Additional Robustness Checks

	Additional robustness check for Column (4) of Table I					
	(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		
MeTootweets 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 I. 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.

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 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.

Robustness Table A7 examines robustness of the results in column (4) of Table I. 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 Appendix A.2).

Column (2) excludes districts with only one or two counties. This ensures that the DD specification picks up the intended within-district effect of the tweets and is not driven by districts with a small number of counties. In columns (3) and (4), counties with a low turnout ($<$ 2,000) and counties with a 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 (see Section A.2). 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.[2]

Finally, column (7) excludes 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 does not change the results.

In Table A8 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 grass-roots sentiments and tweets with overt political angles (e.g., “#bluewave”).

[2] 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 suggests that the results are not simply driven by these pro-Democratic areas.

Limitation: Changing Demographics The above discussion suggests that the MeToo tweets measure is able to capture sentiments on the ground, and do not originate from inauthentic political activity. A limitation on a causal interpretation, however, is in changing demographics. As a falsification test in Section 4.4, I repeat the main results from Table I, but with the 2016 House returns as the dependent variable. Since the MeToo movement in 2018 cannot travel back in time, there should be no detected correlation between the MeToo measure and the 2016 outcomes. Table II reports the results and suggest that the county-level trends detected in Table I already exist in 2016.

One possible explanation is an underlying time trend in Republican counties towards a higher Democratic vote share. Evidence of this trend is also hinted at in Table III to the extent that counties with a higher Republican vote share in the 2016 presidential elections have systematically lower turnout in the 2018 house elections, and in Table A9 to the extent that change in turnout is negatively correlated with the Republican presidential vote share (columns (5)–(6)). Part of this may be driven by cross-county migration or the coming of age of young voters. The results for changes include changes in demographics, using the 5-year estimates from 2012–16 to 2015–19, but these may not fully address underlying trends.

Limitation: County-level Variation Using county-level variation of the MeToo measure and vote shares, in principle, addresses concerns with unobserved confounders at the congressional district level. Moreover, county borders are infrequently adjusted and are therefore not directly affected by gerrymandering present at other geographical delineations. The county-level variation, however, poses two broad problems.

First, the use of the difference-in-differences at the county level relies on MeToo high variation within counties of a district. Districts with low cross-county variation in the MeToo movement and with a low number of counties do not contribute much to the estimation. Trivially, any county that is coterminous with its district does not contribute to identification. The extent to which districts with many counties drive the results implies limitations to generalising the results to the average US county.

A second institution-specific issue is the difference in county vs district border changes. Districts are apportioned by population size every ten years, according to the US Constitution. County borders, however, are more idiosyncratic, infrequently adjusted, and are more determined by historic episodes such as the colonial land grant era than by contemporary population size. The growing urbanisation of the US, the decennial apportionment of the districts, combined with the lack of mandate for county border adjustments imply that suburban and rural districts are geographically large, and tend to contain many counties, while the urban districts are geographically small and contain fewer counties.

Furthermore, the above implies that most counties are more rural, more White, and more Republican, which suggests that the detected effect of the MeToo measure at the county level are concentrated in geographically large areas with a small share of the US voting population. Again, the ancillary tests in the Appendix A.5 attempt to account for some of these issues regarding the variation in county sizes, but do not necessarily address the full problem. To this extent, results involving the additional interaction with the Republican vote share say more about the MeToo movement and the Republican rural and suburban counties rather than the average US county.

A.6 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 county-level 2016–2018 change in the Republican House vote share on turnout.

Table A9 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 (2) and (4), with the change in presidential elections vote share included, 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 ($p < 0.01$), and for the two-party vote share, it is a 0.28 percentage point drop ($p < 0.05$). The drop in the Republican two-party vote share is about half the magnitude of the all-party vote share, consistent with a shift of votes mostly from the independent (rather than Republican) to Democratic.

The estimates for the change in log turnout between 2016 and 2018, 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 ($p < 0.1$).

As a falsification 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

Table A9

Change in Republican Vote Share, District-County Level

	Change in *house* Republicanvote share between 2016 and 2018				Falsification	
	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)	−0.0302***	−0.0288***	−0.0149**	−0.0137*	−0.0033	
	(0.0090)	(0.0088)	(0.0074)	(0.0072)	(0.0027)	
Log tweet density × (Pres. 2012 Rep. vote share)						0.0017
						(0.0028)
Log tweet density	0.4280*	0.4699**	0.1150	0.1536	0.0239	−0.1444
	(0.2332)	(0.1988)	(0.2573)	(0.2175)	(0.0553)	(0.1644)
Change in log(total House votes) 2016–18		−3.0346*		−3.0140*	0.0094	−0.6947**
		(1.6873)		(1.6980)	(0.1008)	(0.2975)
Change in log(total Pres. votes) 2012–16					−2.8255	−1.5249
					(1.9617)	(1.6380)
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	0.8905	0.8953	0.9057	0.9103	0.8766	0.9118
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. County census controls include the 14 demographic variables and additionally the percentage of citizen voting-age population; these are entered as both levels and changes from the ACS 5-year estimates for 2012–16 and the ACS 5-year estimates for 2015–19, except for the percentage rural population available only from the decennial census. The electoral control variables in columns (1)–(4) include the house Republicanvote 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 Republicanvote share from 2008–12. 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 A10

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

	Change in *house* Republicanvote share between 2016 and 2018				Falsification	
	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 tweet density × (Pres. 2016 Rep. vote share)	−0.0433***	−0.0420***	−0.0193***	−0.0180***	0.0001	
	(0.0042)	(0.0041)	(0.0044)	(0.0043)	(0.0018)	
Log tweet density × (Pres. 2012 Rep. vote share)						0.0002
						(0.0019)
Log tweet density	0.2358	0.2735*	0.1271	0.1581	−0.1016**	−0.1270
	(0.1795)	(0.1536)	(0.1978)	(0.1691)	(0.0495)	(0.1110)
Change in log(total House votes) 2016–18		−2.8902*		−2.9657*	0.0165	−0.6768**
		(1.5780)		(1.6621)	(0.1008)	(0.2897)
Change in log(total Pres. votes) 2012–16					−2.6061	−1.3068
					(1.9448)	(1.6144)
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	0.8970	0.9014	0.9069	0.9114	0.8768	0.9121
N	3102	3102	3102	3102	3102	3102

Notes—This Table replicates the regressions in Table A9, 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.

capturing existing downward trends by anti-Republican sentiment—that counties with a high Republican vote share in 2012 are not those with a drop in the 2012–16 presidential Republican vote share.[3]

An increase in turnout and the corresponding decline in the Republican vote share need not necessarily be the primary driving factor for Democratic gains in the 2018 midterm house elections. Political parties may ride on current waves of concern and turn out voters to build up a support base for future election cycles, including the 2020 presidential elections. As is well known, past turnout strongly predicts future turnout, and political parties thus have incentives to turn out partisans even if it is immaterial in the current elections (e.g., Fowler 2006; Coppock and Green 2016).

In Table A10 of the Appendix, I repeat the regressions using log tweets as an intensity measure instead of the log tweets density measure (normalized by county population), and the results are more significant overall, both in terms of economic and statistical significance.

A.7 Extra Figure and Tables

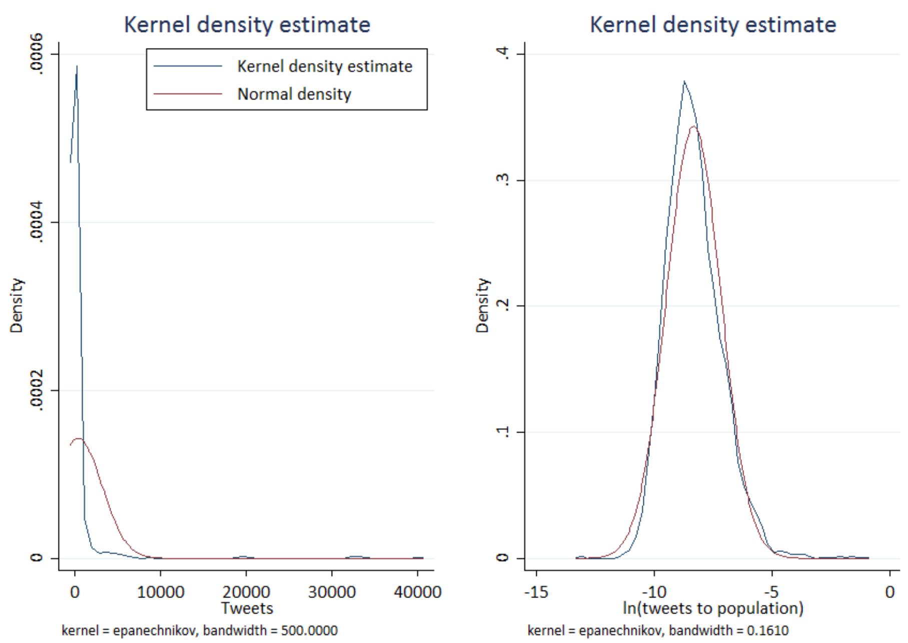

Figure A2: Distribution of MeToo Tweets, by Counties

[3] The falsification tests have the same conclusion when using the all-party presidential Republican vote share.

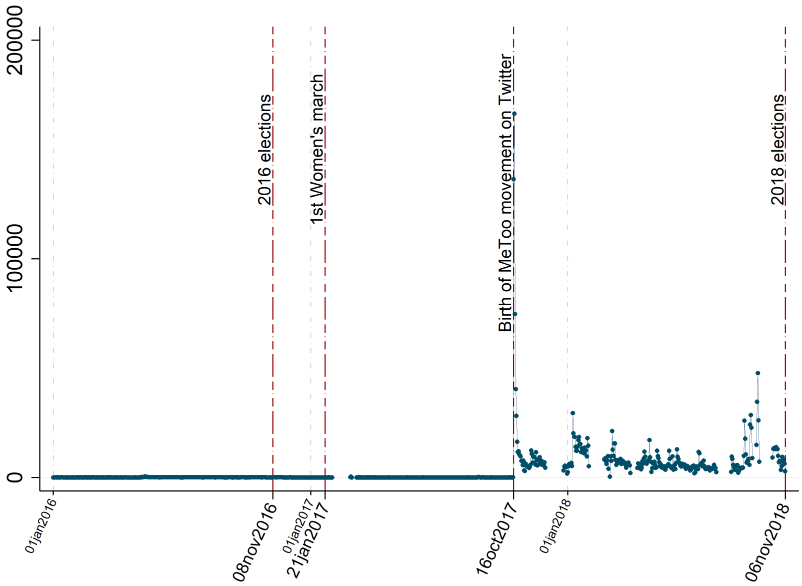

Figure A3: Extended Timeline of MeToo Tweets, Levels

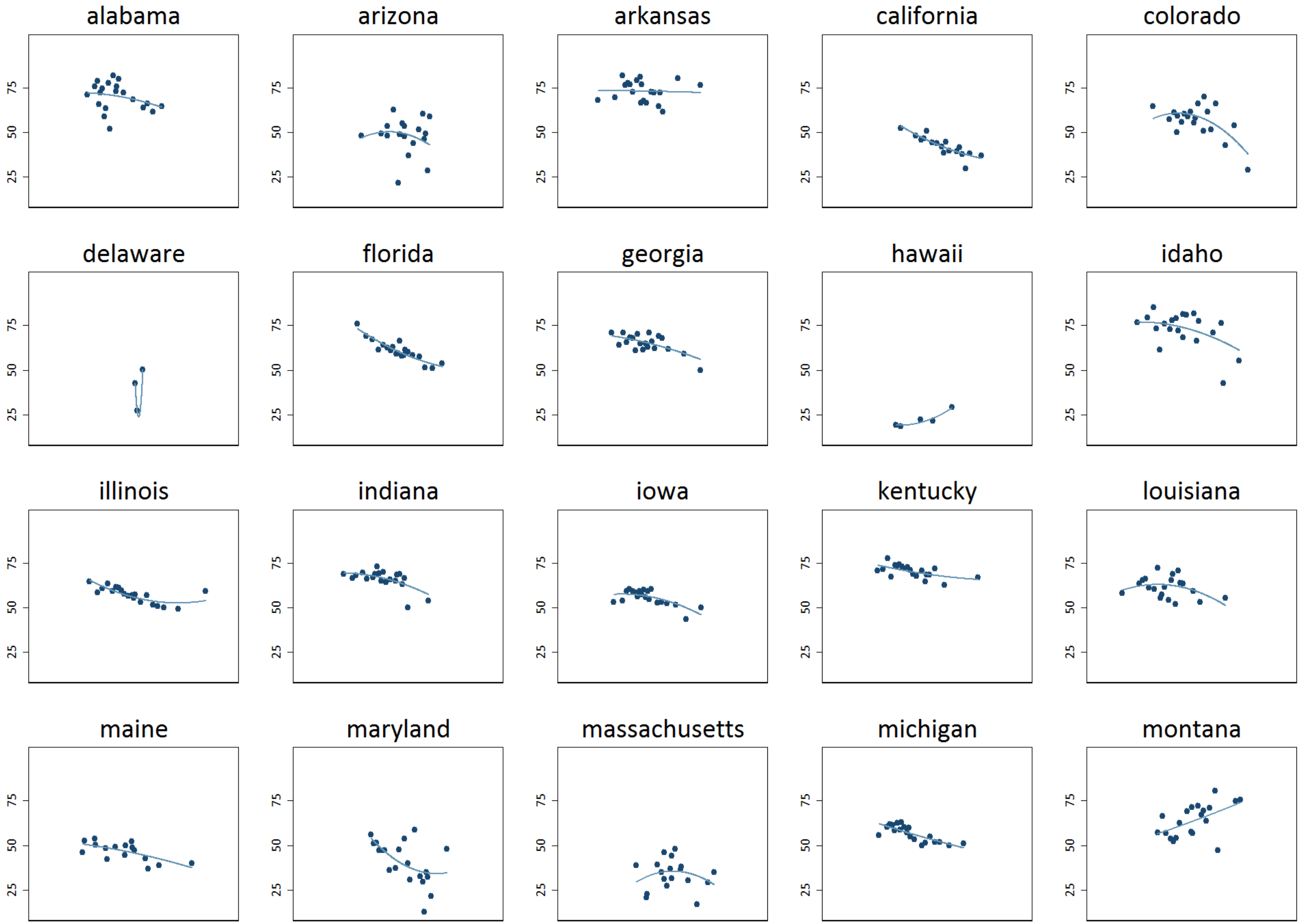

Figure A4: Correlations of Tweets and Republican Vote Share, by State (Part 1)

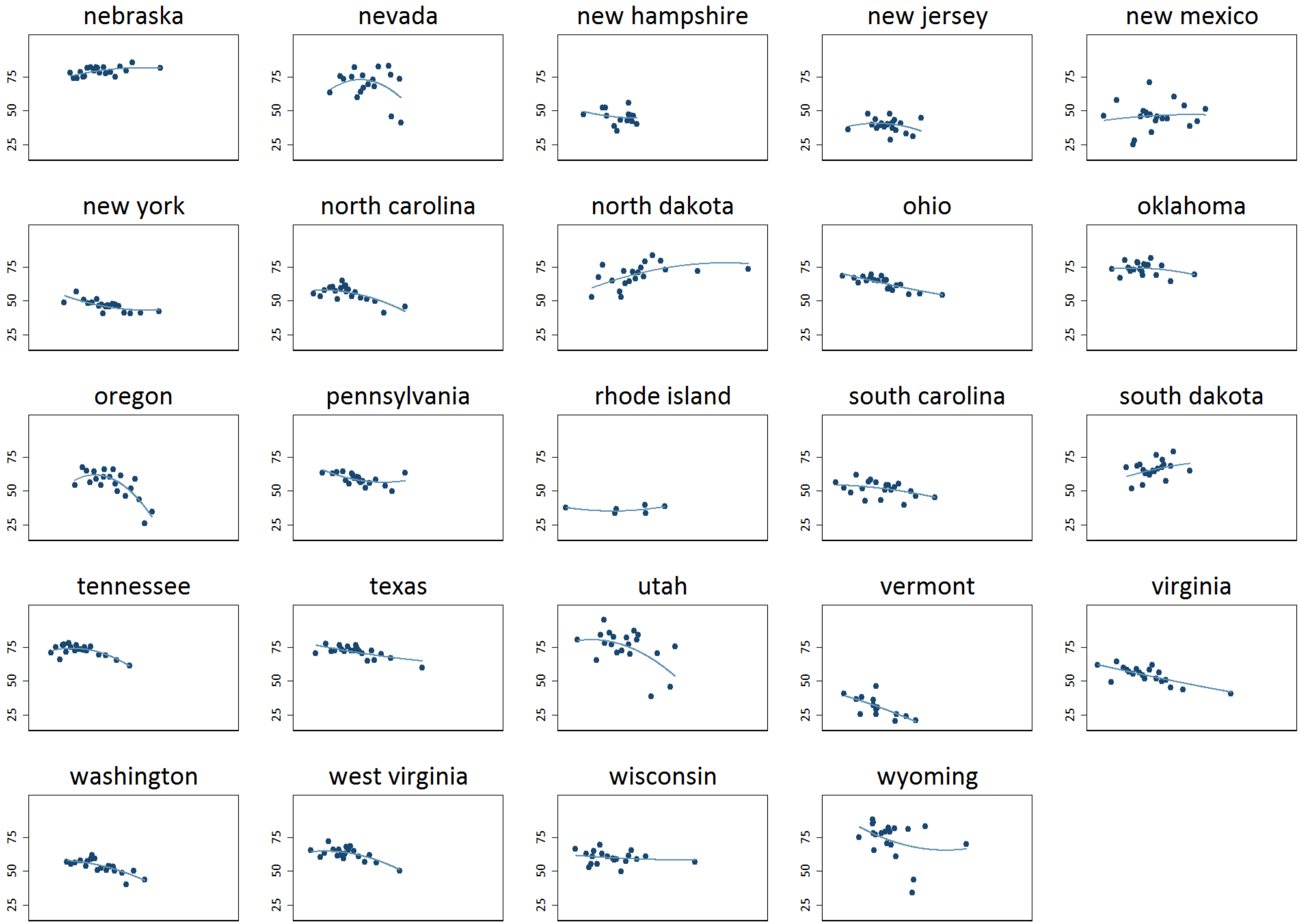

Figure A5: Correlations of Tweets and Republican Vote Share, by State (Part 2)

Table A11

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 Republicanvote share. The coefficients here corresponds column (4) of Table I.
*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A12

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	Split delegation	No senate elections	Battleground states	Rep. & Battleground states	Senate elections (split delegation)	Head-to-head bw. man & woman	Rep. districts & low margin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.031	−0.031	−0.019	−0.015	−0.016	−0.032	-0.083^{*}	−0.025
	(0.033)	(0.033)	(0.032)	(0.036)	(0.032)	(0.032)	(0.050)	(0.032)
Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.050^{***}	0.050^{***}	0.055^{***}	0.054^{**}	0.043^{**}	0.047^{***}	0.115^{***}	0.029^{**}
	(0.017)	(0.017)	(0.015)	(0.023)	(0.018)	(0.016)	(0.036)	(0.014)
Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	-0.026^{***}	-0.026^{***}	-0.021^{*}	−0.020	−0.019	-0.024^{**}	-0.020^{*}	-0.015^{*}
	(0.010)	(0.010)	(0.011)	(0.013)	(0.011)	(0.009)	(0.011)	(0.009)
Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.019	0.019	−0.004	0.012	0.013	0.018	0.014	0.005
	(0.016)	(0.016)	(0.018)	(0.022)	(0.020)	(0.016)	(0.016)	(0.014)
Additional differences by State/District								
I × Rep. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.026	0.026	−0.021	−0.090	−0.097	0.062	0.078	−0.033
	(0.048)	(0.048)	(0.040)	(0.062)	(0.067)	(0.056)	(0.058)	(0.049)
I × Dem. woman × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.012	−0.012	−0.021	−0.019	0.006	0.003	-0.087^{**}	0.077^{*}
	(0.026)	(0.026)	(0.034)	(0.025)	(0.025)	(0.027)	(0.037)	(0.039)
I × Rep. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	0.005	0.005	−0.003	−0.005	−0.012	−0.014	−0.006	-0.052^{*}
	(0.018)	(0.018)	(0.018)	(0.016)	(0.016)	(0.019)	(0.016)	(0.028)
I × Dem. man × (Log tweet density) × (Pres. 2016 Rep. vote share)	−0.013	−0.013	0.043	0.007	0.003	−0.008	−0.005	0.113^{**}
	(0.022)	(0.022)	(0.027)	(0.026)	(0.025)	(0.024)	(0.034)	(0.050)
I × Rep. woman × (Log tweet density)	−0.099	−0.099	1.472	−2.844	−3.070	−2.380	−0.160	2.320^{*}
	(1.680)	(1.680)	(1.174)	(1.775)	(1.870)	(2.259)	(1.510)	(1.223)
I × Dem. woman × (Log tweet density)	0.081	0.081	0.657	0.416	−0.046	−0.245	1.282^{*}	-1.340^{*}
	(0.561)	(0.561)	(0.672)	(0.556)	(0.580)	(0.552)	(0.662)	(0.727)
I × Rep. man × (Log tweet density)	0.405	0.405	0.245	−0.416	0.304	0.850^{*}	0.043	0.932
	(0.477)	(0.477)	(0.496)	(0.463)	(0.432)	(0.460)	(0.441)	(0.613)
I × Dem. man × (Log tweet density)	−0.246	−0.246	-1.287^{*}	0.598	0.349	−0.335	0.861	-2.016^{**}
	(0.745)	(0.745)	(0.756)	(0.763)	(0.727)	(0.822)	(1.060)	(0.807)
Control variables								
Candidate fixed effects	X	X	X	X	X	X	X	X
2016 House & 2012–16 Pres. election	X	X	X	X	X	X	X	X
County census demographics	X	X	X	X	X	X	X	X
Racial & gender voting	X	X	X	X	X	X	X	X
Main-party candidates only	X	X	X	X	X	X	X	X
R^2	0.952	0.952	0.952	0.952	0.952	0.951	0.953	0.952
N	6185	6185	6185	6185	6185	6185	6185	6185

Notes—This Table replicates columns (3)–5) of Table I, except that an additional interaction is entered into the model to capturing any differences of the MeTooeffect 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 battleground states defined as states with less than a 10% margin in the 2016 presidential elections, and where the Republican candidate won; in column (6), it is for states with senate elections and where there is split delegation (one Democratic and one Republican senator); in column (7), 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 (8), it is for Republican districts where the winning margin is less than 10% in the 2016 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.

Table A13

THE INTENSIVE AND EXTENSIVE MARGINS OF METOOMOVEMENT

	This Table breaks down the tweet density into MeTootweets per MeTooauthor and MeTooauthors per population		
	All-party	Two-party	
	(1)	(2)	(3)
Log MeTootweets per MeTootwitter			
Log tweets per twitter × (Pres. 2016 Rep. vote share) × (Rep. woman)	−0.142*	−0.092	−0.135*
	(0.081)	(0.077)	(0.079)
Log tweets per twitter × (Pres. 2016 Rep. vote share) × (Dem. woman)	0.134***	0.102**	0.050
	(0.048)	(0.040)	(0.042)
Log tweets per twitter × (Pres. 2016 Rep. vote share) × (Rep. man)	−0.119***	−0.076***	−0.035
	(0.028)	(0.025)	(0.026)
Log tweets per twitter × (Pres. 2016 Rep. vote share) × (Dem. man)	0.100***	0.064**	0.037
	(0.032)	(0.032)	(0.033)
Log MeTootwitter density			
Log twitter density × (Pres. 2016 Rep. vote share) × (Rep. woman)	0.018	−0.006	0.010
	(0.031)	(0.024)	(0.027)
Log twitter density × (Pres. 2016 Rep. vote share) × (Dem. woman)	0.009	0.031**	0.040**
	(0.016)	(0.015)	(0.018)
Log twitter density × (Pres. 2016 Rep. vote share) × (Rep. man)	0.003	−0.006	−0.021
	(0.011)	(0.011)	(0.014)
Log twitter density × (Pres. 2016 Rep. vote share) × (Dem. man)	−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 I, except that in this Table the log tweet density measure is decomposed into a log MeTootweets per MeTooauthor and a log MeTooauthor density (log MeTooauthor 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.