The Impact of the Women's March on the U.S. House Election*

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Abstract

Three million people participated in the Women's March against discrimination in January 2017, the largest single-day protest in the history of the United States. The inaugural event sparked a grassroots political movement with the goal of increasing the representation of women and other marginalized groups in the political sphere. We show that protesters in the 2017 march increased political preferences for women and people from ethnic minorities in the 2018 House of Representatives Election. Using machine-chosen daily weather shocks as exogenous drivers of attendance at the 2017 march, we find that protesters increased turnout at the House Election and the vote shares obtained by marginalized groups, particularly women, irrespective of their party affiliation. We conclude that protests can help to empower historically underrepresented groups through changes in local political preferences.

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INTRODUCTION

Three million people participated in the Women's March of 2017, the largest single-day protest in U.S. history (Fisher et al., 2019). According to organizers, the goal was to "send a bold message to our new administration on their first day in office that women's rights are human rights." Previous research has shown that protests affect the policy-making process and local policy support (Madestam et al., 2013; Enos et al., 2019), but less is known about whether these collective actions are able to empower historically underrepresented and marginalized groups. In this paper we estimate the local impact of protesters on women and people from ethnic minorities who ran for office in the 2018 House of Representatives Elections. Representation matters because its impact on policies is well documented (Chattopadhyay and Duflo, 2004; Beaman et al., 2012; Clayton, 2021). Yet those who run and are elected for office rarely match the diversity in the population.[1]

The analysis proceeds in four steps. First, we measure the number of protesters per county using the Crowd Counting Consortium (Chenoweth and Pressman, 2017). These data aggregate information from local news, law enforcement statements, online event pages, and photos of the March. Second, we use daily weather shocks as exogenous drivers of protest attendance. Crucially, after accounting for a vector of predetermined socio-demographic characteristics, these weather shocks are unrelated to previous political outcomes including the vote share of women and other underrepresented groups in the 2016 House Election. We interpret this evidence as suggesting that the weather residuals are conditionally exogenous and can then be used for causal identification of political impacts. Third, we use these shocks to estimate the impact of the Women's March on the 2018 House Election. We find that the share of protesters in the population is causally associated with higher turnout and vote share for candidates from historically underrepresented groups. And fourth, we show that protesters increased the vote share of women irrespective of their party affiliation and that Non-Hispanic and Non-African American women benefited more.

We begin by using the research design proposed by Madestam et al. (2013) which employs an

[1]Less than 20% of candidates were women or from ethnic minorities in the 2016 House Election, even though these groups represent 50 and 38% of the U.S. population (Bialik and Krogstad, 2017; Dittmar, 2018). The gender gap in politics goes beyond the United States and affects most countries in all continents (World Economic Forum, 2020). See Dal Bó et al. (2017) for a thorough study of who becomes a politician.

indicator for rainfall as an instrument for attendance to the Tea Party protest (April 15, 2009). In contrast to their findings, we show that rainfall fails to predict attendance to the Women's March (January 21, 2017). This result can be explained by differences in the geographic distribution of rainfall between the day of the Tea Party protest and the day of the Women's March, or different motives behind these protests, among others. Building on this design and the work of Gilchrist and Sands (2016), we create a vector of weather shocks and choose the best predictors of local protest attendance using the least absolute shrinkage and selection operator proposed by Belloni et al. (2011). The "machine-chosen" weather shock corresponds to the deviation from the historical average temperature in a county-month, and it is empirically a strong predictor of attendance to the March. Importantly, when measured in years without a Women's March (2011-2016) this temperature shock is uncorrelated with protest participation, providing further support for the design.

Using the machine-chosen weather shock as an instrument for the local intensity of the Women's March in 2017 in a instrumental variables framework, we find that protesters increased the vote share of women and candidates from marginalized groups, irrespective of their party affiliation. More precisely, we estimate that 1,000 additional protesters – the observed size of the average protest in a county – increased the vote share of women and minorities by approximately 13 percentage points (3,000 more votes) in a county, close to 32% of the sample mean. This effect is distributed evenly across women from the Republican and Democratic parties. Moreover, the size of this estimate is similar to comparable studies measuring the impact of protest size using the number of protesters in the local population (Madestam et al., 2013; González, 2020).

What is the explanation behind the impact of 2017 protesters on the 2018 election? Leading narratives posit that sustained local organizing activity arising from the inaugural Women's March was key (Putnam and Skocpol, 2018). We provide empirical support for this hypothesis by showing that the intensity of the march persisted locally into 2018. We also show that the intersectionality of the march faded away when looking at the vote shares obtained by minority women. In fact, most of the change in voting patterns can be explained by an increase in the vote for white women (2,500 votes) with the remaining increase being explained by additional votes for man from ethnic minorities. This is, women candidates from marginalized groups do *not* appear to systematically benefit from the political impacts of the march.

Our analysis addresses empirical concerns related to omitted variables and measurement error in local protests. However, we still need to face the possibility of a potential violation of the exclusion restriction. A leading concern mentioned in previous literature is media coverage, perhaps affected by the weather and likely to affect electoral outcomes (Strömberg, 2015). To study this possibility we checked if protests were covered by the local news in counties with the lowest and highest temperature shocks. We found local news for virtually all counties. Most importantly, we followed Gentzkow and Shapiro (2010) and constructed a new county-level dataset with media articles covering the March and found that the number of articles is unrelated to the weather shock we use as instrument. Unfortunately, it is impossible to test for all possible threats. Thus we allow for a direct effect of the shock and calculate that it would have to be relatively large to make the impact of protesters indistinguishable from zero (Conley et al., 2012).

This paper makes two contributions. First, we add to a growing literature studying under-represented groups and ways to improve their representation. Our main contribution is to show that collective actions such as protests can empower these groups by pushing citizens to vote for them. The majority of studies look at the case of women and estimate the impact of gender quotas, the composition of recruiting committees, and the presence of female-leadership in politics on women's candidacies (Duflo, 2005; Beaman et al., 2009; Broockman, 2009; Bagues and Esteve-Volart, 2010; Gilardi, 2015; O'Brien and Rickne, 2016; Baskaran and Hessami, 2018). Similarly, researchers have also studied the impact of women in politics on the selection of policies, the provision of public goods, violence against women, women's entrepreneurship, women's political careers, and the educational attainment of girls, finding mostly improvements in women's lives (Chattopadhyay and Duflo, 2004; Beaman et al., 2012; Iyer et al., 2012; Ferreira and Gyourko, 2014; Ghani et al., 2014; Brollo, 2016; O'Connell, 2018, 2020; Clayton, 2021). Another part of this literature focuses on similar issues but studies minority women or historically under-represented groups different from women, both in the United States and other parts of the world (McAdam, 1982; Pande, 2003; Sass and Mehay, 2003; Banducci et al., 2004; Segura and Bowler, 2006; Preuhs, 2006; Hughes, 2011; Washington, 2012; Dunning and Nilekani, 2013).

Finally, we contribute to our understanding of the impacts of protests and other collective actions on society more generally. Recent research has shown that local collective actions such as protests and riots can affect the implementation of policies, vote shares, political attitudes, women's position within households, and property values (Collins and Margo, 2007; Aidt and Franck, 2015; Mazumder, 2018; Bargain et al., 2019; González, 2020; González and Vial, 2021; Reny and Newman, 2021).[2] In contrast to previous research, we focus on the impact of protesters on the empowerment of underrepresented and marginalized groups in the public sphere.

CONTEXT

The Women's March in the U.S.

The first Women's March took place on January 21st 2017 and more than three million people participated, making the event the largest single day protest in U.S. history (Chenoweth and Pressman, 2017). At the beginning, many interpreted the rallies as tied to the election of the Republican Donald Trump as President. However, the organization of this massive event was made possible by the sustained work of many activist organizations and interest groups who had experience fighting women's historical marginalization (Berry and Chenoweth, 2018).[3] It was precisely these grassroots organizations which transformed the March into an intersectional movement.[4]

What were the main reasons to protest? Surveys reveal that more than half of participants declared women's rights to be a top motive for demonstrating, while politics was only the 8th out of 13 possible causes (Fisher et al., 2017). In between these two, protesters mentioned Equality, Reproductive Rights, Environment, Social Welfare, Racial Justice, and LGBTQIA issues. These motives point to a connection between demonstrations and a desire to improve the representation

[2] A related literature estimates the impact of *violent* protests, i.e. riots. Some recent work uses modern identification strategies and finds that violence helps protesters to achieve their goals (Huet-Vaughn, 2020; Enos et al., 2019) and some that it shifts votes towards conservative candidates (Wasow, 2020). Earlier work uses descriptive analyses and provides mixed findings (Shorter and Tilly, 1971; Welch, 1976; Snyder and Kelly, 1976; Button, 1978; Isaac and Kelly, 1981; Frey et al., 1992; McAdam and Su, 2002; Franklin, 2009; Chenoweth and Stephan, 2012).

[3] Other events also contributed to build momentum. An example is the Facebook page which exploded with RSVP created by Teresa Shook from Hawaii and similar event pages in other parts of the U.S. (Stein, 2017).

[4] Examples of these organizations include progressive groups linked to Hillary Clinton and Bernie Sanders campaigns, Planned Parenthood, and the National Organization for women, among others.

of women and other groups. In fact, according to Beyerlein et al. (2018) "[The Women's March] reflected widely felt grievances and outrage over Trump's election. Not only were women's bodies being threatened, but so were the rights of immigrants, people of color, workers, and the LGBTQIA community."

The Women's March returned in January of 2018 with almost two million protesters. The main theme before this new event was to take the "Power to the Polls" with the explicit goal set by leading organizations to "register 1 million new voters and help elect more women to office" (Chira, 2021). Although there were factions from the initial organization, the intersectionality of the movement remained a key characteristic. In the years that followed, the march continued as an annual event held in January, but the number of participants has gradually decreased.

Representation and the 2018 Election

Women, African-Americans, Hispanics, Asians/Pacific Islanders, and Native Americans have been historically underrepresented in the U.S. Congress. In fact, underrepresented groups different from women constitute 31% of the population but occupied only 12% of all seats in the 107th Congress in 2001. Similarly, women occupied only 13% of seats (Bialik and Krogstad, 2017). Representation has improved but it is still far from matching the U.S. population.

In terms of representing the U.S. population, the 2018 Midterm Elections were record-breaking. According to studies from the Pew Research Center, the 116th U.S. Congress resulted in the most racially and ethnically diverse in American history, also breaking the record number of women serving on it (Desilver, 2018; Bialik, 2019). Overall, out of 535 members, 116 of the elected lawmakers were non-white, representing an 84% increase with respect to the 107th Congress of 2001-03. For the first time, African and Native Americans paired their share of total population with their share of Representatives in the House (12% and 1% respectively). Moreover, not only was the number of congresswomen elected the highest in U.S. history, it was also the biggest jump in women members since the 1990s. This can be easily seen in the fact that more than a third of the 102 elected women were newcomers to the House of Representatives.

The potential impact of the Women's March on votes for candidates from marginalized groups has been hypothesized based on previous research studying the impact of the Tea Party protests (Madestam et al., 2013). In fact, Chenoweth and Pressman (2018) give three reasons to expect similar or larger impacts: (i) more participants in the Women's March, (ii) more durable participation, and (iii) broader and enduring resistance to Donald Trump and his policies.

ANALYSIS

Data and Summary Statistics

To measure the number of protesters per county we use Erica Chenoweth and Jeremy Pressman's Data in Crowd Counting Consortium (CCC, Chenoweth and Pressman 2017; Fisher et al. 2019). The authors used publicly reported estimates of participants validated using local news, law enforcement statements, event pages on social media, and photos of the protests. When reports were imprecise, they aimed for conservative counts. This multi-sourced approach avoids problems of underreporting when using one or two newspapers (Bond et al., 1997, 2003) by allowing to check and validate the information, something particularly important for crowd counting (Fisher et al., 2019). Because the CCC reports are originally at the city level, we aggregated these to the county level to match the outcomes we examine. Most cities belong to a single county, hence this aggregation was straightforward, and when this was not the case we assigned the city to the county with the largest share. Reports were pulled together if more than one city protested within a county.

We downloaded the weather data from the National Oceanic and Atmospheric Administration (NOAA). In particular, we examine all days in January from 2011 to 2017, from nearly 6000 different weather stations in the U.S., and match each county with its nearest station. The large vector of weather variables we use pushes us to drop some stations with incomplete weather data. Besides a wide vector of weather variables, we also construct variables for the amount of rain on January 21st 2017 and indicator variables for whether that day was rainy or not, using a threshold of 0.10 inches. All in all, we create a vector of 50 weather-related variables. We interpret these as weather *shocks* because we define them as the deviation from their average in January in previous years. Among these we find temperature and precipitation.[5] We divide temperature and rainfall shocks in bins of 2°F and 0.25 inches respectively.

We also construct demographic and electoral variables to use as controls. In terms of demographics, we gather county-level data for population density, income, unemployment, change in unemployment between 2013-2017, and the share of urban, Hispanic, African-American, white, and foreign-born population. Given that our focus is on the *Women*'s March, we also gather data for the share of female population, share of female citizens, and share of unmarried partners households. These data come from the U.S. Census Bureau and the American Communities Survey. We also construct log-distance from each county to Washington D.C., where the main Women's March took place, and electoral variables. For the latter we use the 2016 U.S. Presidential Election and 2014 House of Representatives Election. The variables comprehend Trump's and Clinton's vote shares, the Republican and Democratic Party vote shares and turnout per county population.

The outcomes are related to the 2018 House of Representatives Elections, data we gather from the Harvard Dataverse (Pettigrew, 2018). We observe the names of all candidates, their political parties, and turnout. We construct three outcome variables. (i) the vote shares obtained by women, (ii) the vote shares obtained by candidates from underrepresented groups, and (iii) turnout. The underrepresented groups in this study include women, African-Americans, Hispanics, Asian/Pacific Islanders, and Native Americans. To determine whether candidates represented minority groups, we use data from The Asian Pacific American Institute for Congressional Studies (APAICS), blackwomeninpolitics.com, NALEO Educational Fund ("Election 2018 Races to Watch: The Power of Latino Candidates"), and "History, Art & Archives, U.S. House of Representatives." When needed, we complement this information with data from the candidates' websites.

[TABLE 1 ABOUT HERE]

Table 1 presents summary statistics for counties with protesters during the Women's March and counties with zero protesters. Counties with protests have a lower share of white population, a larger share of foreign born and Hispanic population, and host more educated people with higher

[5] We use average and maximum temperature and exclude minimum temperatures because they usually occur during the night and protests take place during the day.

median income and less unemployment. Politically, counties with and without protests have similar turnout, but the former are more Democrat and voted relatively more for women and other underrepresented groups in the previous election. Therefore a simple comparison of counties with and without protests is unlikely to reveal the political impact of the Women's March.

Research Design

To estimate the impact of the Women's March on political participation and preferences, we use an instrumental variables framework. The relationship of interest can be written as follows:

$$Y_i = \alpha + \beta \cdot \text{Protesters}_i + x_i'\delta + \epsilon_i \tag{1}$$

where Y_i is an outcome of interest in county i, the Women's March variable is $Protesters_i$ and measures the intensity of the local protest, x_i is a vector of predetermined control variables, and ϵ_i is a mean-zero error term clustered by state. As discussed, a naive OLS estimation of β is unlikely to represent the causal effect of protests because of omitted variables and measurement error in the number of protesters. An instrumental variables strategy can help to overcome both concerns.

Unusual weather the day of the Women's March is likely to have had an impact on protest attendance and, we argue, it is also likely to be uncorrelated with other factors driving attendance to the march and electoral outcomes. The former condition is testable, but the latter is ultimately an (identification) assumption. As argued by previous research, there are two leading concerns regarding this assumption. First, weather shocks are likely to affect the local press coverage of the protest. Second, the weather might affect protesters' experience during the event and affect the spread of the movement. The next section discusses why both of these threats are unlikely to be relevant in this context and presents evidence to support this claim.

To begin the analysis we replicate Madestam et al. (2013)'s first stage strategy:

$$\text{Protesters}_i = \phi + \beta \cdot \text{Rain}_i + \zeta \cdot \text{Likelihood of Rain}_i + x_i'\lambda + \varepsilon_i \tag{2}$$

where $Protesters_i$ is a measure of attendance to the march in county i. $Rain_i$ is an indicator for at least 0.1 inches of rain the day of the event, or the amount of inches of rain fallen that day. $Likelihood\ of\ Rain_i$ is a flexible control for the probability of rain calculated using daily weather data from previous years. The vector x_i contains pre-determined county characteristics, including past electoral outcomes and demographic characteristics. The estimates are weighted by population when the protesters variable is per capita. Standard errors are clustered at the state level, but results are robust to adjusting standard errors for spatial correlation with a distance cutoff of 100 kilometers. Since rainfall is likely to decrease attendance to the rallies, we expect $\widehat{\beta}$ to be negative.

The effect of rainfall on protest attendance depends on the geographic distribution and the strength of rainfall during the day under study. A more robust strategy is to follow Gilchrist and Sands (2016) and use weather shocks selected by a data-driven algorithm. We use the least absolute shrinkage and selection operator (LASSO) method proposed by Belloni et al. (2011) to select weather instruments from a set of 50 weather shocks.[6] In particular, we estimate:

$$\text{Protesters}_i = \omega + \beta \cdot \text{Weather Shock}_i + w_i'\lambda + \varepsilon_i \tag{3}$$

where $Weather\ Shock_i$ are the LASSO-chosen instruments. The chosen variable is the standardized temperature shock the day of the inaugural march.[7] Figure 1 presents a map with the variation of this shock after removing the variation from the vector of machine-chosen control variables.[8]

[FIGURE 1 ABOUT HERE]

Importantly, the machine-chosen weather shock has little empirical relationship with previous electoral variables after conditioning for demographic characteristics. Columns 5 and 6 in Table 1 present estimates of equation (3) using county characteristics as dependent variable. As control

[6]A similar strategy has also been used by Beraja et al. (2021). Lennon et al. (2021) use simulation to show that the use of linear machine-learning methods work better than non-linear ones such as random forests.

[7]In particular, this shock is defined as $z_i \equiv \frac{x_i - \bar{x}_i}{\sigma_i}$, where x_i is the average temperature in county i the day of the Women's March and $\bar{x}_i, \sigma_i$ are the average and standard deviation of x_i calculated using five random days in January during the seven years before the march. Table A.1 presents the vector with all possible weather shocks to be chosen.

[8]Figure A.1 shows the geographic distribution of the temperature shock without residualizing. This map reveals spatial correlation in the temperature shock. To address this potential threat to inference in the appendix we show that results are robust when excluding one state at the time, when we cluster standard errors by state in all specifications, and when we allow errors to be correlated spatially with different geographic cutoffs using Conley's (1999) method.

variables w_i, we use all demographic variables available in our dataset. The estimates in these columns reveal that w_i is important because (i) all electoral differences across counties disappear after including w_i in the estimation (panel B, column 6), and (ii) the weather shock affected counties with less foreign population, more African Americans, and more Hispanics (panel A, column 5). Therefore, it is important to include demographic characteristics as control variables. To improve the power of our estimates, we select these demographics using an algorithm and allow it to potentially also choose predetermined electoral variables as additional controls.[9]

RESULTS

Attendance to the March

Table 2 presents estimates of equations (2) and (3) to test for the impact of weather shocks on attendance to the March. Columns 1-4 replicate Madestam et al.'s (2013) econometric strategy using the number of protesters in the county over population as the endogenous variable. Columns 1, 3, and 4 measure the number of protesters using an estimate from a variety of sources – what the CCC reports call "Best guess" – and column 2 uses the lowest reported number ("Low estimate").

[TABLE 2 ABOUT HERE]

The results indicate that rainfall the day of the event has little predictive power on the size of local protests. If anything, the sign of the relationship is the opposite of what we expected. We highlight three possible explanations for this (null) result. First, the randomness of daily weather shocks means that the set of counties affected by it might be different during the inaugural protest of the Tea Party Movement and the Women's March. Second, the Women's March was six times larger than the Tea Party protest (Beyerlein et al., 2018). Hence, the sensitivity of attendance to rainfall might differ due to the differential motives behind each protest, their size, and the time of the year in which they took place. And third, different types of weather shocks might be important for turnout decisions in January versus April.

[9] There are 24 demographic characteristics and 10 electoral predetermined variables to be potentially chosen as controls. Table A.2 presents all of these and Table A.3 shows the set chosen for each outcome. Results are similar if we use the controls employed by Madestam et al. (2013).

In contrast to the rainfall shock, the machine-chosen temperature shock has a strong predictive power on protest participation (see Table 2, column 5). The results in this column indicate that a one standard deviation (σ) increase in the temperature shock (0.84) decreases the share of protesters in the population by 0.43 percentage points (pp., $0.51 \times 0.84 = 0.43$). This coefficient represents a 43% change with respect to the sample average and the associated F-statistic is 17.[10] Moreover, in the appendix we show that the temperature shocks in January 21 of previous years (2011-2016) are empirically unrelated with the number of protesters in 2017, with inconsistent coefficients that are smaller in magnitude and sometimes positive or negative (Table A.5).

Why is protest attendance lower with unusually large temperatures? Our interpretation is that the relative price of participating in a protest increases with warmer temperatures during the winter. High temperatures presumably make protesting less attractive because of an increase in the opportunity cost of alternative outdoor activities. Although there is little direct evidence of substitution within the set of outdoor activities, there is some indirect evidence consistent with this notion. In particular, outdoor recreational activities increase with warmer temperatures (Graff Zivin and Neidell, 2014), presumably crowding out protest activities. Moreover, this increase in recreational activities is particularly important during winter times (Obradovich and Fowler, 2017; Chan and Wichman, 2020).

Political Impacts

Table 3 presents the main results of our analysis. Panel A shows the direct effect of the machine-chosen instrument on the outcomes of interest, candidates' vote shares (columns 1-2), and county turnout (column 3).[11] Panel B uses the instrument in a two-stage least squares framework to estimate the impact of protesters, and panel C shows OLS results for comparison purposes. Panel A indicates that a one standard deviation increase in the temperature shock on January 21st (i.e. 0.84) decreased women's vote share and the vote share of underrepresented groups by 4 percentage

[10]Table A.4 show that these results are similar if we measure the number of protesters in thousands or in logarithms. Figure A.2 shows that the non-parametric relationship between the temperature shock and protest attendance is approximately linear across the shock distribution.

[11]Table A.5 complements the reduced-form results by showing the lack of a relationship between the temperature shock in January 21 of previous years and the electoral outcomes we examine.

points, and decreased turnout by 0.7 pp. In terms of magnitude, each of these estimates represent changes of 18%, 13% and 2% of the sample means respectively.

[TABLE 3 ABOUT HERE]

Instrumental variables estimates in panel B indicate that the local intensity of the march had an impact on the electoral outcomes of underrepresented groups. To gauge their magnitude, let us consider an increase of 1 pp in the share of protesters in a county, i.e. approximately 1,000 more protesters which represents the size of the average protest in counties with these events. According to these estimates, protesters increased the vote share of underrepresented groups by 13 pp (3,000 votes) in the average county. We note that the size of our 12.95 estimate (s.e. 5.63) is remarkably similar to the impact of the Tea Party protesters on the vote share of the Republican Party (i.e. 12.59 and s.e. 4.21) in the comparable specification (see Table VI column 2 in Madestam et al. 2013). Most of this increase is explained by an increase in the vote share of women, who got 10 percentage points additional vote share (i.e. 2,500 votes). Panel C reveals that a naïve OLS estimation delivers an attenuated coefficient which could be explained by classical measurement error in the number of protesters, omitted variables, or the characteristics of the compliers.

Beyond political preferences, protests could also have had an impact on local political participation. Column 3 examines this dimension and reveals that in counties with more intense protests citizens were indeed motivated to vote, increasing turnout by 1.5 pp or 1,500 votes. This result is consistent with the organizers' goal of increasing political participation.

Robustness

The impact of the Women's March on turnout and vote shares obtained by underrepresented groups are robust findings which are *not* driven by subsets of data points. First, we estimate similar impacts when we exclude any single state from the estimation, suggesting that outliers or specific states are not driving the results. Figure A.4 presents the robustness of two-stage least squares estimates and, for completion, Figure A.5 presents the first-stage.[12] Second, the impacts of the March are

[12]The exception is perhaps the case of California in which case the estimates become larger. California experienced a low temperature shock, high attendance to the March, and it is highly populated, all of which contribute to this effect.

also robust to the exclusion of outliers. To implement this exercise we omit from the estimation all counties for which $|DFBETA_i| < \frac{2}{\sqrt{N}}$, where N is the number of observations and the term in absolute value represents the difference between estimates with and without county i in the estimation. Table A.6 present estimates omitting these outliers and results are the same.

We also obtain similar findings when using alternative sets of controls and inference procedures. We reach similar statistical conclusions when we select control variables ourselves instead of using a machine algorithm. Table A.7 presents the most demanding of these specifications in which we use Madestam et al.'s (2013) controls plus a vector of women-related variables and estimated coefficients are virtually the same. And finally, our conclusions are again similar if we allow for spatial correlation in the error term. Table A.8 presents results using arbitrary correlation structures within 100 and 50 km and the statistical significance remains unchanged.

DISCUSSION

Given that the inaugural Women's March in 2017 and the House Election in 2018 were separated by more than 22 months, what could explain the impact of protesters on political outcomes? Existing narratives suggest that the emergence of local grassroots movements led by certain groups of women were key. This section studies the role of sustained political activity emerging from the 2017 march, together with the role of partisanship, and minority groups within women. We also put alternative explanations related to local media under empirical scrutiny. We conclude that the march created sustained organized activity locally, increased political preferences for women irrespective of their party affiliation, and white women were benefited more in terms of vote shares.

Sustained Organized Activity

Sustained organizing activity at the local level seems to have played a crucial role in explaining our findings. In fact, Putnam and Skocpol (2018) found evidence in local interviews that led them to conclude that college-educated white women were key: "[W]hat is underway is a national pattern of mutually energizing local engagement. Sociologically, what we are witnessing is an inflection point – a shift in long-standing trends – concentrated in one large demographic group, as college-educated women have ramped up their political participation *en masse*." The emergence of grassroots organizations is a leading narrative to explain the sustained engagement of protesters after the 2017 march (Stockman, 2018). Political organizations linked to the Women's March in 2018 worked closely with local organizers to increase turnout.

We test for the political sustainability of the march at the local level by looking at the size of protests one year after the inaugural event, i.e. in January 20 of 2018. If the organizing political activity remained, we should observe a causal link between the number of protesters across years. To test for this, we again use the CCC reports to construct comparable measures of protest size for all counties and estimate equation (1) using instrumental variables. The average of this variable reveals that local protests decrease their size from 1% of protesters in the population in 2017 to 0.5% in 2018. The difference with the previous analysis is that we now replace political outcomes in the House Election as dependent variable by the number of protesters in 2018 (instead of 2017) over population. An estimated coefficient $\widehat{\beta} > 0$ supports the local sustainability of the march.

Column 1 in Table 4 presents the reduced form, instrumental variables estimates, and OLS results for comparison. The estimated coefficients support the hypothesis of sustained organized activity. The number of protesters in 2017 is causally associated with the number of protesters in 2018 (p-value<0.01). Moreover, the coefficient $\widehat{\beta} = 1.10$ can be interpreted as an elasticity: and additional 1 pp of protesters in the population in 2017 delivers 1.1 pp more protesters in 2018. These findings are consistent with recent experimental findings supporting the existence of persistent political engagement during protest movements (Bursztyn et al., 2021).

[TABLE 4 ABOUT HERE]

These results, together with leading narratives revolving around the Women's March, raise the question of whether these protests increased the vote shares of the democratic party or simply women more generally. They also suggest that white women might have been benefited in terms of vote shares more than non-white women. Below we put these hypotheses under empirical scrutiny.

Political Parties and Intersectionality

Did protesters at the 2017 march increased the vote shares of specific candidates or political parties? The local organizations which emerged from the inaugural march worked with the goal of increasing turnout and women's vote shares at the 2018 election. Nevertheless, their progressive agenda makes it natural to argue that their political preferences were more aligned with Democratic rather than Republican candidates. Moreover, the higher turnout also suggests that Democrats might have benefited more, according to previous research (Hansford and Gomez, 2010).

To test for the impact of protesters on votes for Republicans and Democrats, we use the same research design and women's vote share as dependent variable but separate the latter by political party. Columns 3 and 4 in Table 4 shows that protesters increased the vote shares of women from both the Democratic and Republican parties (p-values<0.01). For comparison purposes, we also use our design to estimate the impact on the vote share obtained by all Democrats (men and women combined). Column 2 shows these results and reveal a null relationship between protesters and the vote share of Democrats. Moreover, the instrumental variables estimates are remarkably similar in columns 3 and 4 and we cannot reject that they are equal. These results show that protesters increased preferences for women irrespective of their party affiliations.

[TABLE 5 ABOUT HERE]

Another discussion around the inaugural 2017 march was related to the role played by white women. Initially, the march was criticized by being organized mostly by white women, who had voted relatively more for Donald Trump in the preceding election and who were accused of linking the march's demands to issues related to their group. Although efforts were made to make white women more aware of racial problems, to include women of color in the movement, and to agree on shared principles to fight for, some historically marginalized groups remained skeptical (Brewer and Dundes, 2018). Eventually the movement became an "intersectional coalition of seasoned activists" with a racially diverse leadership (Fisher et al., 2017), but how this intersectionality translated into votes for different groups remained an open question.

To test for the impact of protesters during the inaugural march on votes for different marginalized groups of women, we estimate equation (1) by instrumental variables and using the vote share of different groups as dependent variable. Columns 4-7 in Table 5 present estimates and show that most of the previously documented increase in women's vote shares comes from higher vote shares for Non-Hispanic and Non-African American women. This is, in counties with more protesters in 2017 the additional support for underrepresented groups favored predominantly white women, with a somewhat smaller increase in votes for African-American men and Hispanic men. In all, the evidence suggests that the intersectionality of the movement faded in their way to the polls.

The Media and Other Explanations

So far our analysis assumes that unusual weather on January 21 of 2017 affected the 2018 election only through attendance to the Women's March. Unusual weather can, however, also change media coverage, which in turn affects electoral outcomes (Snyder and Strömberg, 2010; Strömberg, 2015). We argue that the media is unlikely to threaten our results for several reasons. In the first place, media coverage of the March should be less affected by unusual weather than past protests because of its contextual relevance and the rise of the internet.[13] In this sense, the fact that rainfall has little impact on attendance is reassuring of the March's importance. In the second place, we manually investigated media coverage of the March in counties with weather shocks above the 90th percentile and below the 10th percentile and found media reports for all protests but two (Tables A.9 and A.10). And most importantly, we collected new data on media articles about the Women's March and found these to be uncorrelated with the temperature shock.

To construct the county-level dataset with the number of articles covering the March, we first download all articles available in ProQuest which mentioned the Women's March during the three months before and after January 21 of 2017. Then, we follow Gentzkow and Shapiro (2010) to match each article to a county, dropping foreign articles. Last, we count the number of articles in each county before and after the March. Overall, we found almost 8,000 articles coming from 224

[13] According to surveys conducted by the Pew Research Center, the percentage of Americans with access to the internet has increased from less than 50% in 2000 to 90% in 2020 (Pew Research Center, 2019).

counties, 20% of which were written before January 21 and 80% after that date.

We test for the relationship between the temperature shock and the number of articles using a cross-sectional dataset at the county-level. Columns 1 and 2 in Table 6 show the lack of a relationship between these variables. Empirically, we estimate equation (3) using as dependent variable the number of articles in the county, the controls from the main specification, and add a control for the number of articles before January 21 of 2017. In particular, column 1 uses as dependent variable an indicator that takes the value of one if there was at least one article covering the Women's March in the three months after and zero otherwise, while column 2 follows Burbidge et al. (1988) and uses the hyperbolic sine transformation of the number of articles. The estimates reveal the lack of a relationship between both variables, with both point estimates being virtually zero and confidence intervals that reject relatively small changes in media coverage.

Another concern relates to how temperatures affect the social experience of protesters at the protest. A large literature has shown that unusually high temperatures make humans more violent (Hsiang et al., 2013). Additionally, violence could affect the protesting experience or its effectiveness at the eyes of the general public. This is unlikely to be a concern in our case because we find that people are *less* likely to join the Women's March with high temperatures. In line with this statement is the fact that 95-99% of all protests were peaceful and arrest-free (Fisher et al., 2019).

Unfortunately, we cannot prove if unusual weather affected elections *only through* attendance to the March. Thus we also calculated the change in our estimates if the instrument had a *direct* impact on electoral outcomes (Conley et al., 2012). To make the impact of the March non-different from zero, the direct effect of the instrument would have to be 18, 47, and 49% of the reduced form effects for the main outcomes. Because these direct effects are non-negligible, we conclude that our estimates of the March's impact are robust to small deviations from the identification assumption.[14]

CONCLUSION

We have shown that protesters can empower historically underrepresented groups and improve their political representation through changes in local political preferences. Crucially, we show

[14]Figure A.3 provides more details about this exercise and the full set of results.

that these changes in preferences are irrespective of party affiliations. The findings in this paper have at least three implications. First, previous research has shown that changes in the representation of groups in the population leads to policy changes, hence we should expect historically underrepresented groups to benefit from their improved representation. Second, having more Congresswomen elected can potentially help to reduce stereotypes and the negative bias in female leaders' effectiveness. Finally, although we focus on high-profile political positions, the Women's March could have also impacted the private sector and lower rank positions.

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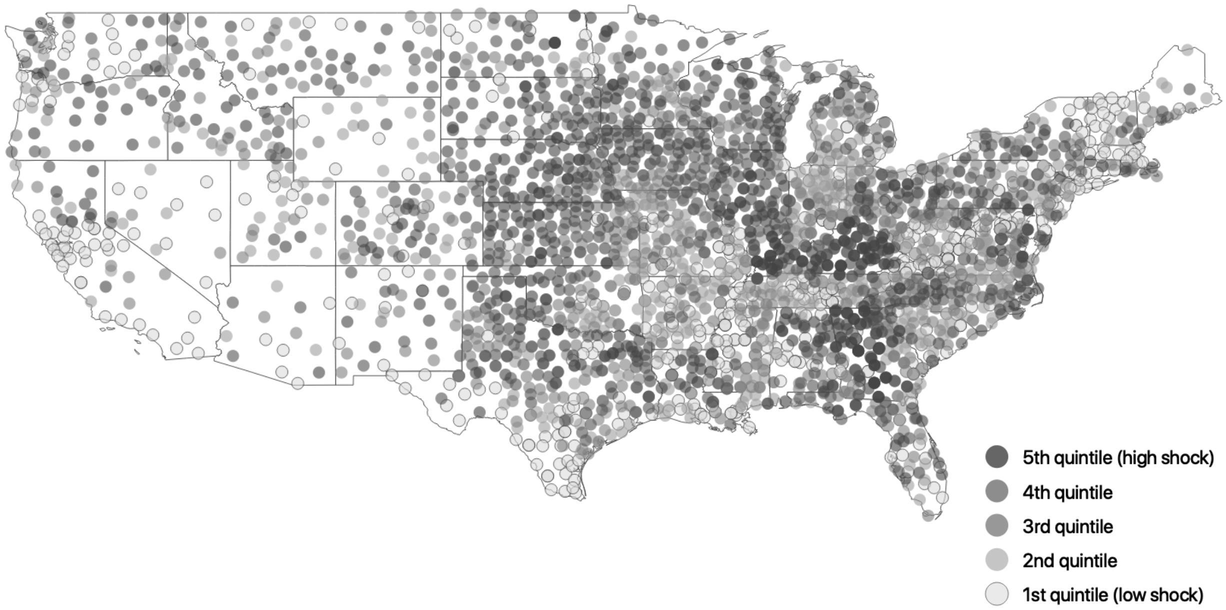
Figure 1: Geographic distribution of weather shocks



Notes: This map shows the residuals of the standardized and residualized temperature shock on January 21st, 2017. Each dot represents the weather shock in a county. Colors denote the intensity of the residualized weather shock. We calculate these residuals after adjusting for a vector of LASSO-chosen and predetermined county characteristics.

Table 1: Descriptive statistics

	All	Counties with protests	Counties without protests	Difference (3)-(2)	Lasso-chosen weather variable: Unconditional exogeneity	Lasso-chosen weather variable: Conditional on demographic characteristics
Panel A – Demographic characteristics	(1)	(2)	(3)	(4)	(5)	(6)
Female population (%)	50.77	50.87	50.67	0.19	0.27***	–
	(1.26)				[0.05]	
Foreign-born population (%)	38.37	46.87	29.67	17.19	-20.35***	–
	(33.89)				[3.99]	
African American population (%)	12.54	12.25	12.84	-0.59	4.01***	–
	(12.77)				[0.82]	
Hispanic population (%)	17.74	21.99	13.39	8.60	-10.57***	–
	(17.22)				[1.04]	
White population (%)	73.12	69.90	76.41	-6.51	4.16**	–
	(16.50)				[1.91]	
Median household income (log)	10.93	10.97	10.90	0.07	-0.06***	–
	(0.26)				[0.02]	
Unemployment rate (%)	5.26	5.12	5.41	-0.29	0.03	–
	(1.66)				[0.10]	
Education, less than college (%)	69.75	66.79	72.78	-6.00	1.48***	–
	(10.78)				[0.47]	
Panel B – Electoral characteristics						
Democrat vote share in 2014 (%)	45.74	51.06	40.30	10.77	-4.95***	2.08
	(21.10)				[1.26]	[1.93]
Republican vote share in 2014 (%)	50.41	44.77	56.18	-11.41	6.02***	-0.87
	(20.66)				[1.26]	[1.59]
Turnout in 2014 (%)	24.13	23.45	24.83	-1.38	2.06**	-0.37
	(7.74)				[0.94]	[0.53]
Hillary Clinton vote share in 2016 (%)	48.48	54.98	41.82	13.17	-6.06***	0.47
	(17.04)				[1.33]	[0.58]
Donald Trump vote share in 2016 (%)	45.92	38.99	53.01	-14.01	7.06***	0.72
	(17.02)				[1.12]	[0.77]
Turnout in 2016 (%)	42.21	41.75	42.67	-0.92	2.20***	-0.81**
	(7.63)				[0.74]	[0.38]
Women vote share 2016 (%)	20.29	24.66	15.80	8.86	-4.19***	0.96
	(22.88)				[1.11]	[1.45]
Underrepresented groups vote share 2016 (%)	33.40	38.99	27.65	11.34	-8.37***	-0.28
	(28.79)				[1.51]	[1.71]
Counties	2,940	470	2,470	2,940	2,940	2,940

Notes: Column 1 presents means and standard deviations in parenthesis. Column 2 (3) present means for counties with a positive (zero) number of protesters on January 21st, 2017. All means are weighted by population. Column 4 presents the difference between columns 2 and 3. Columns 5 and 6 present the cross-sectional correlation between the lasso-chosen weather variable (i.e. temperature shock) and the corresponding county characteristics, with standard errors presented in square brackets; column 5 presents the unconditional correlation and column 6 conditional on all demographic characteristics.

Table 2: The effect of weather shocks on attendance to the Women's March

	Dependent variable: 2017 protesters in population (%)				
	(1)	(2)	(3)	(4)	(5)
Rainy protest indicator	0.18	0.14		-0.43	
	(0.30)	(0.28)		(0.47)	
Rainfall			-0.03		
			(0.19)		
LASSO-chosen weather variable					-0.51***
					(0.12)
Counties	2,936	2,936	2,936	466	2,940
R-Squared	0.240	0.208	0.239	0.375	0.132
F-Statistic	0.37	0.26	0.02	0.85	17.55
Protesters Variable	Best Guess	Low Estimate	Best Guess	Best Guess	Best Guess
Sample counties	All	All	All	Protesters>0	All
Election controls	Y	Y	Y	Y	N
Demographic controls	Y	Y	Y	Y	N
Machine-chosen controls	N	N	N	N	Y
Avg. dependent variable	1.00	0.79	1.00	1.98	1.00

Notes: The unit of analysis is a county. A rainy protest is defined based on the precipitation amount on January 21st, 2017. The rainy protest indicator equals one if there was more than 0.1 inches of rain. Rainfall in column 3 is the precipitation amount in inches. The variable chosen by LASSO is the standardized average temperature shock: January 21st, 2017's average temperature deviation from its mean, divided by its standard deviation. Robust standard errors in parentheses clustered at the state level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: The Women's March and the 2018 House Election

	Vote shares obtained by		
	Women	All underrepresented groups	Turnout (%)
	(1)	(2)	(3)
Panel A – Reduced Form			
LASSO-Chosen weather variable	-4.95***	-5.30***	-0.81***
	(1.28)	(1.30)	(0.27)
Panel B – Two-stage least squares			
2017 protesters in population (%)	9.62***	12.70**	1.50***
	(3.44)	(5.48)	(0.56)
Panel C – Ordinary least squares			
2017 protesters in population (%)	0.98*	0.19	0.10
	(0.51)	(0.35)	(0.06)
Counties	2,940	2,940	2,940
Avg. dependent variable	27.90	41.30	35.02
Machine-chosen controls	X	X	X

Notes: All outcomes are measured in the 2018 House Election. The LASSO-chosen weather variable is the standardized average temperature shock: January 21 of 2017's average temperature deviation from its mean, divided by its standard deviation. The outcomes are: the vote shares obtained by women in column 1, and by candidates that belong to an underrepresented group in politics in column 2 – i.e. women, Hispanic, African-American, Asians/Pacific Islanders or Native Americans – and turnout in the same election in column 3. The unit of analysis is always a county. All regressions are population weighted and include LASSO-chosen controls for each specification. Standard errors in parentheses are clustered at the state level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Persistence and partisanship

	Protesters in 2018	All democrats	Women vote share by party: Democrats	Women vote share by party: Republicans
	(1)	(2)	(3)	(4)
Panel A – Reduced Form				
LASSO-Chosen weather variable	-0.57***	0.27	-2.91***	-2.21***
	(0.15)	(0.34)	(1.04)	(0.78)
Panel B – Two-stage least squares				
2017 protesters in population (%)	1.10***	-0.59	5.66**	4.29**
	(0.18)	(0.77)	(2.31)	(1.98)
Panel C – Ordinary least squares				
2017 protesters in population (%)	0.34***	-0.02	0.96*	0.01
	(0.07)	(0.14)	(0.56)	(0.07)
Counties	2,940	2,940	2,940	2,940
Avg. dependent variable	0.51	53.10	22.36	5.10
Machine-chosen controls	X	X	X	X

Notes: All outcomes are measured in the 2018 House Election. The LASSO-chosen weather variable is the standardized average temperature shock: January 21 of 2017's average temperature deviation from its mean, divided by its standard deviation. The outcomes are: the vote shares obtained by all candidates from the Democratic Party in column 2, by women from the Democratic Party in column 3, and by women from the Republic Party in column 4. The unit of analysis is always a county. All regressions are population weighted and include LASSO-chosen controls for each specification. Standard errors in parentheses are clustered at the state level. Statistical significance: *** p <0.01, ** p <0.05, * p <0.1.

Table 5: Interpretation of results

	Women vote share by underrepresented group			
	Hispanic	Non Hispanic	African American	Non African American
	(1)	(2)	(3)	(4)
Panel A – Reduced Form				
LASSO-chosen weather variable	-0.73	-4.14***	2.09**	-6.04***
	(0.63)	(1.13)	(0.81)	(1.43)
Panel B – Two-stage least squares				
2017 protesters in population (%)	1.31	7.38***	-4.96**	14.36***
	(1.12)	(2.44)	(2.28)	(4.94)
Panel C – Ordinary least squares				
2017 protesters in population (%)	-0.03	0.89*	0.13	0.56
	(0.13)	(0.44)	(0.35)	(0.42)
Counties	2,940	2,940	2,940	2,940
Avg. dependent variable	2.26	25.64	4.95	22.95
Machine-chosen controls	X	X	X	X

Notes: All outcomes are measured in the 2018 House Election. The LASSO-chosen weather variable is the standardized average temperature shock: January 21 of 2017's average temperature deviation from its mean, divided by its standard deviation. The outcomes in columns 1-4 are the vote shares obtained by Hispanic women, Non-Hispanic women, African American women, and Non-African American women. The unit of analysis is always a county. All regressions are population weighted and include LASSO-chosen controls for each specification. Standard errors in parentheses are clustered at the state level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Weather shocks and media coverage of the march

	Indicator for at least 1 article about the march	Logarithm of number of articles about the march
	(1)	(2)
LASSO-Chosen weather variable	0.00	0.01
	(0.02)	(0.06)
Counties	2,940	2,940
Machine-chosen controls	X	X

Notes: All regressions are population weighted and include LASSO-chosen controls for each specification. Standard errors in parentheses are clustered at the state level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ONLINE APPENDIX

The Impact of the Women's March on the U.S. House Election

Magdalena Larreboure and Felipe González

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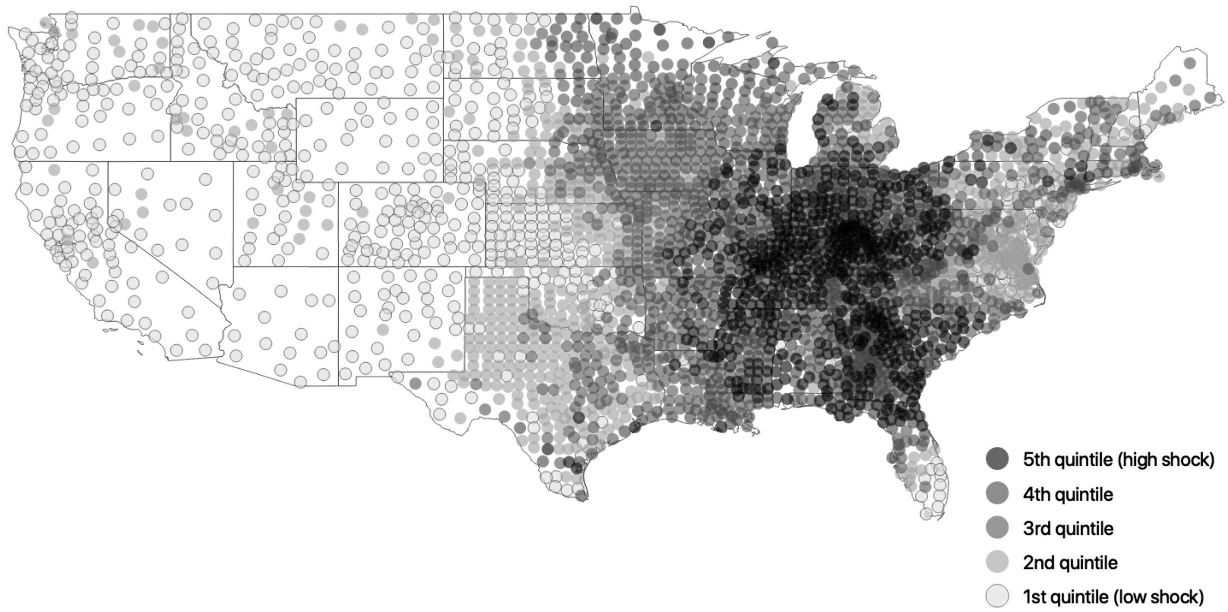
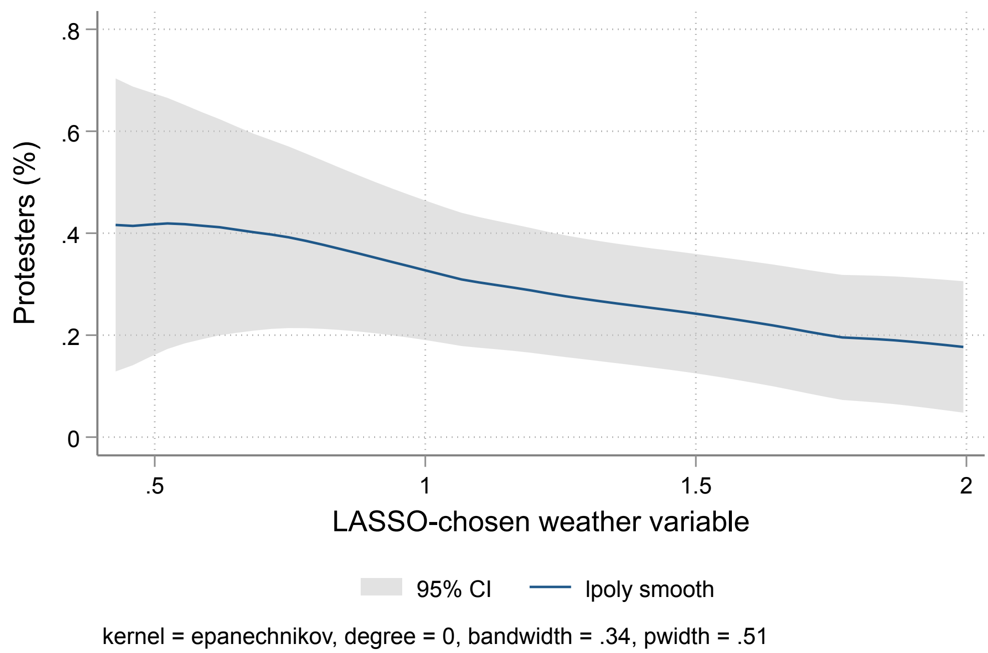
Figure A.1: Temperature shock without residualizing



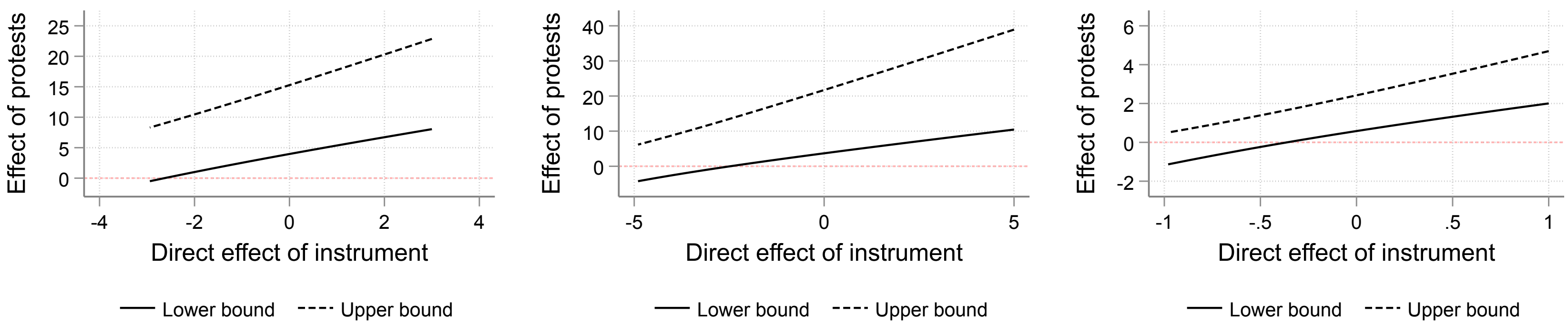
Notes: Geographic distribution of temperature shocks on January 21, 2017. This shock is defined as $z_i \equiv \frac{x_i - \bar{x}_i}{\sigma_i}$, where x_i is the average temperature in county i the day of the Women's March and $\bar{x}_i, \sigma_i$ are the average and standard deviation of x_i calculated using five random days in January during the seven years before the March.

Figure A.2: Non-parametric first stage



Notes: Non-parametric estimates from a local polynomial estimation. The *y*-axis "Protesters (%)" is the share of protesters per capita in a county. The *x*-axis is the Lasso-chosen instrument, i.e. the average temperature in January 21 of 2017 minus the mean in previous years, divided by its standard deviation. The counties included in this analysis are all of which experienced a temperature shock (the instrument) between the 10th and 90th percentiles of the instrument.

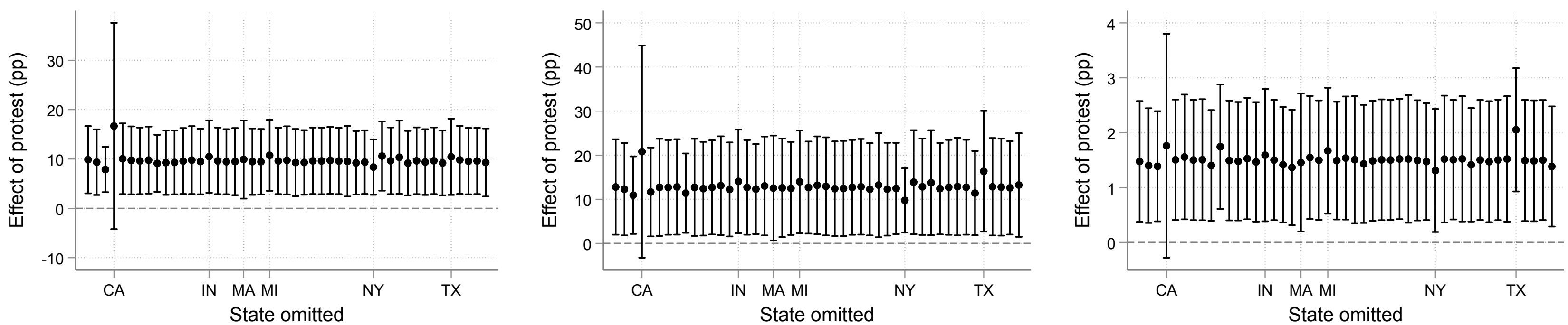
Figure A.3: Plausible exogeneity test



(a) Women vote share (%)   (b) Underrepresented groups vote share (%)   (c) Turnout 2018 (%)

Notes: These figures present results from a bounding exercise in which we allow the temperature shock to affect outcomes directly. The x-axis measures (theoretical) direct effects of temperature shock on women's vote share (Panel A), underrepresented groups' vote share (Panel B) and Turnout (Panel C). The y-axis measures the corresponding effect of protests. Overall, we find that to make the effect of protests non-different from zero the direct effect of the instrument would have to be -2.6 in Panel A, -2.5 in Panel D and -0.4 in Panel E, equivalent to 18% (-2.6/-4.96), 47% (-2.5/-5.32) and 49% (-0.4/-0.81) of the reduced form effects.

Figure A.4: Robustness of two-stage estimates



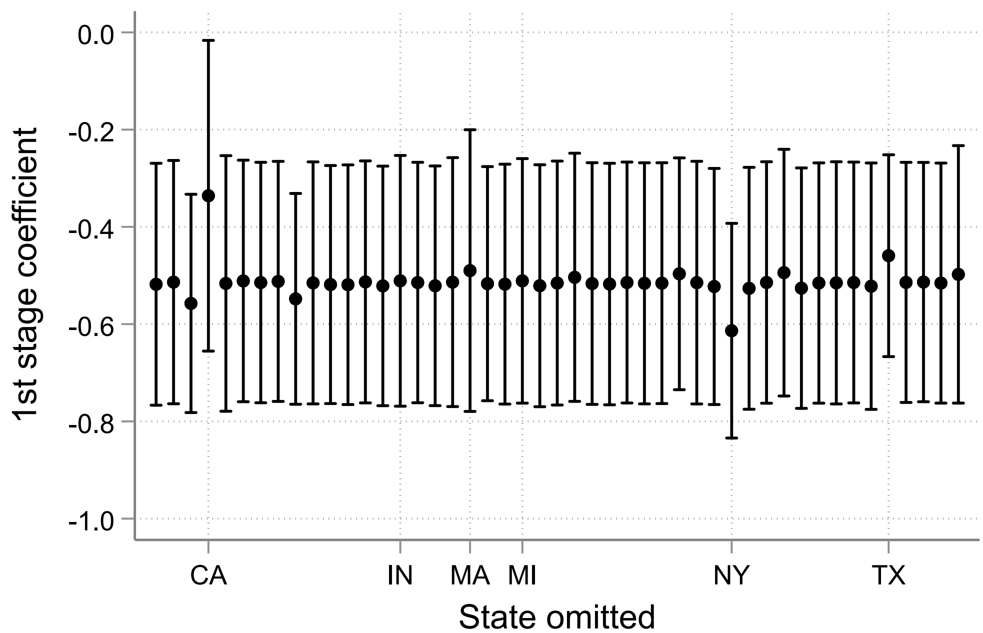
(a) Women's vote share (%)

(b) Underrepresented group vote share (%)

(c) Turnout (%)

Notes: Figure A.4 presents the results of Table III, Panel B, when omitting one state at a time. Underrepresented Group includes Women, Hispanics, African-Americans, Asians/Pacific Islanders and Native Americans.

Figure A.5: Robustness of first-stage



Notes: Figure A.5 presents the First Stage results, when omitting one state at a time.

Table A.1: Vector of weather shocks - possible instruments

Description	Average Temperature	Maximum Temperature	Rain
Deviation from historical mean	Shock	Shock	Shock
Squared shock	Squared shock	Squared shock	Squared shock
Cubed shock	Cubed shock	Cubed shock	Cubed shock
Shock divided by historical standard deviation	Standardized shock	Standardized shock	Standardized shock
Squared shock divided by historical sd	Squared shock standardized	Squared shock standardized	Squared shock standardized
Absolute value of shock divided by historical sd	Absolute value shock standardized	Absolute value shock standardized	Absolute value shock standardized
Shock bins	Shock bins (1-5)	Shock bins (1-6)	Shock bins (1-16)
Dummy for each bin	5 2F shock bins	6 2F shock bins	16 0.25 inches rain shock bins
Indicator for any rain			Any rain
Indicator for any snow			Any snow

Table A.2: Vector of possible controls

Demographic	Electoral
Female population (%)	Clinton vote share
Family households (%)	Trump vote share
Foreign-born population (%)	Votes for Clinton (% of population)
Median household income (log)	Votes for Trump (% of population)
Unemployment rate (%)	Turnout 2016
Unemployment change (2013-2017)	Democratic Party vote share (2014)
African American population (%)	Republican Party vote share (2014)
Hispanic population (%)	Votes for DP 2014 (% of population)
Population density (log)	Votes for RP 2014 (% of population)
Rural population (%)	Turnout 2014
White population (%)	
Female citizens (%)	
Unmarried partners households (%)	
Distance to Washington DC (log)	
10 deciles of population dummies	

Table A.3: Machine-chosen controls

	LASSO-chosen controls	Number of controls not chosen
County-level analysis		
Women	Democratic Party Vote Share (2014), Republican Party Vote Share (2014), Votes for DP 2014 (% of population), Unemployment Rate (%), Second Decile Population, Ninth Decile Population	28
Underrepresented groups	Clinton Vote Share, Votes for Trump (% of population), Democratic Party Vote Share (2014), Republican Party Vote Share (2014), Votes for DP 2014 (% of population), Unemployment Rate (%), Ninth Decile Population	27
Turnout 2018 (%)	Turnout 2016, Turnout 2014, Democratic Party Vote Share (2014), Republican Party Vote Share (2014), Votes for DP 2014 (% of population), Unemployment Rate (%), First Decile Population, Ninth Decile Population	26

Notes: The flexible controls for population size are dummies for each decile on the variable's distribution (i.e. Second Decile Population is an indicator for having a low share of population, corresponding to the second decile in the population size distribution.)

Table A.4: Alternative specifications for the first-stage

	Protesters (%)			Protesters (thousands)			Log protesters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LASSO-chosen weather variable	-0.51***	-0.24**	-0.13	-41.63***	-19.22***	-40.80***	-0.47***
	(0.12)	(0.09)	(0.44)	(13.59)	(5.83)	(11.73)	(0.11)
Counties	2,940	2,940	470	2,940	2,940	470	441
F-Statistic	17.55	7.20	0.08	9.38	10.87	12.11	17.40
Protesters Variable	Best Guess	Low Estimate	Best Guess	Best Guess	Low Estimate	Best Guess	Best Guess
Sample counties	All	All	Protesters>0	All	All	Protesters>0	Protesters>0
Avg. dependent variable	1.00	0.79	1.98	1.06	0.84	6.62	0.99
Machine-chosen controls	X	X	X	X	X	X	X

Note: The unit of analysis is a county. The instrument chosen by LASSO is the Standardized Average Temperature Shock: January 21st, 2017's average temperature deviation from its mean, divided by its standard deviation. Controls are also LASSO-chosen, and are mainly composed by previous electoral outcomes, flexible dummies for population and measures of unemployment. Best Guess denotes the average turnout across the three estimations of attendance data. Low estimate is the derived most conservative count of the turnout in any given location. Regressions in columns 1-3 are population weighted. Robust standard errors in parentheses, clustered at the state level.

Table A.5: Temperature shocks in previous years

	Temperature shock in January 21 of year:						
	2011	2012	2013	2014	2015	2016	2017
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Protesters in 2017 over population (%)	0.28	0.07	-0.03	0.19	-0.00	0.41**	-0.51***
	(0.23)	(0.11)	(0.15)	(0.27)	(0.22)	(0.19)	(0.12)
Protesters in 2018 over population (%)	0.27	-0.08	0.15	0.41*	0.15	0.26*	-0.57***
	(0.18)	(0.09)	(0.11)	(0.21)	(0.20)	(0.14)	(0.15)
Women's vote shares (%)	2.78	-1.98	-0.64	0.30	-0.71	2.31	-4.95***
	(1.95)	(1.56)	(2.09)	(1.83)	(2.33)	(2.02)	(1.28)
Underrepresented groups vote shares (%)	1.24	0.27	1.80	1.65	2.23	0.44	-5.30***
	(1.49)	(1.55)	(2.43)	(1.24)	(2.31)	(2.03)	(1.30)
Turnout (%)	-0.09	-0.05	-0.36	0.69**	0.09	1.41***	-0.81***
	(0.73)	(0.42)	(0.42)	(0.34)	(0.38)	(0.46)	(0.27)

Note: The unit of analysis is a county and each coefficient (s.e.) comes from a separate first-stage or reduced form regression in which we measure the temperature shock in different years. The temperature shock is January 21's average temperature deviation from its mean, divided by its standard deviation. Controls are also LASSO-chosen, and are mainly composed by previous electoral outcomes, flexible dummies for population and measures of unemployment. Column 7 corresponds to the first-stage and reduced forms in the main analysis of the paper. Standard errors in parentheses are clustered at the state level.

Table A.6: Robustness of 2SLS results to excluding outliers based on their DFBETA

	Vote shares obtained by		
	Women	All underrepresented groups	Turnout (%)
	(1)	(2)	(3)
Protesters (%)	7.78***	9.88**	1.24**
	(2.37)	(4.68)	(0.53)
Counties	2,748	2,748	2,748
Avg. dependent variable	27.90	41.30	35.02

Note: This table shows the effect of protests, instrumented with a LASSO-chosen instrument, on the Electoral Outcomes when excluding observations based on their DFBETA. Following the standard approach, we exclude all observations for which $|DFBETA_i| < \frac{2}{\sqrt(N)}$ where N is the number of observations. The unit of analysis is a county. All regressions are population weighted and include LASSO-chosen controls for each specification. Robust standard errors in parentheses, clustered at the state level.

Table A.7: Robustness of results to human-selected controls

	Vote shares obtained by		
	Women	All underrepresented groups	Turnout (%)
	(1)	(2)	(3)
Panel A – Reduced Form			
LASSO-Chosen weather variable	-3.23**	-5.43***	-0.70**
	(1.59)	(1.62)	(0.30)
Panel B – Two-stage least squares			
Protesters (%)	9.54	16.05*	2.08
	(6.84)	(9.39)	(1.52)
Panel C – Ordinary least squares			
Protesters (%)	0.59	0.39	0.02
	(0.41)	(0.31)	(0.06)
Counties	2,940	2,940	2,940
Avg. dependent variable	27.90	41.30	35.02

Note: LASSO-Chosen weather variable is a temperature shock on January 21, 2017. The outcomes are the vote shares obtained by women candidates and candidates from underrepresented group in politics: Women, Hispanic, African-American, Asians/Pacific Islanders or Native Americans, and turnout for the 2018 House of Representatives Election. The unit of analysis is a county. All regressions are population weighted and include the same controls as in Madestam et al. (2013) plus a vector of women-related controls. Robust standard errors in parentheses, clustered at the state level.

Table A.8: Robustness of results to spatial correlation

	Vote shares obtained by		
	Women	All underrepresented groups	Turnout (%)
	(1)	(2)	(3)
Panel A – Distance cutoff: 100 kms			
Protesters (%)	9.62***	12.70**	1.50***
	(3.04)	(6.41)	(0.49)
Panel B – Distance cutoff: 50 kms			
Protesters (%)	9.62**	12.70	1.50***
	(4.47)	(8.16)	(0.54)
Counties	2,940	2,940	2,940
Avg. dependent variable	27.90	41.30	35.02

Note: This table shows the effect of Protests, instrumented with a LASSO-chosen instrument, on the Electoral Outcomes with standard errors adjusted for spatial correlation, as proposed by Conley (1999), using Collela et al. (2019)'s program. We use distance cutoffs for the spatial kernel of 100kms in Panel A and 50kms in Panel B. The unit of analysis is a county. All regressions are population weighted and include LASSO-chosen controls for each specification. Robust standard errors in parentheses, adjusted for spatial correlation.

Table A.9: Local reports of protesters in counties with *high* temperature shocks

County ID	Value of the instrument	Protesters (%)	Local report	Local newspaper
(1)	(2)	(3)	(4)	(5)
12001	2,51	0,76	Y	The Gainesville Sun
12073	2,05	5,50	Y	Tallahassee Democrat
17019	2,17	2,56	Y	The News Gazette
17031	2,06	4,78	Y	Chicago Tribune
17077	2,05	3,22	Y	The Southern Illinoisan
17089	2,06	0,11	N	–
17143	2,09	0,93	Y	WMBD News
18003	2,27	0,27	Y	The Journal Gazette
18097	2,31	0,71	Y	Indiana Public Media
18127	2,11	0,22	Y	The Times of Northwest Indiana
18157	2,22	0,47	Y	Journal and Courier
18167	2,29	0,18	Y	Tribune Star
21035	2,09	1,81	Y	WKMS
21067	2,14	2,27	Y	WKYT
21111	2,04	0,65	Y	Courier Journal
26077	2,32	0,56	Y	M Live
26161	2,06	3,34	Y	Ground Cover News
39035	2,19	1,20	Y	Cleveland.com
39095	2,10	0,05	Y	The Blade
42049	2,31	1,15	Y	Goerie.com
45077	2,10	0,41	Y	Independent Mail
47157	2,03	0,61	Y	Memphis Flyer

Notes: Own construction.

Table A.10: Local reports in counties with *low* temperature shocks

County ID	Value of the instrument	Protesters (%)	Local report	Local newspaper
(1)	(2)	(3)	(4)	(5)
4005	-0,64	1,75	Y	Arion Daily Sun
4019	-1,33	1,55	Y	Tucson.com
6007	-1,34	0,84	Y	Chico Enterprise Record
6013	-0,90	0,54	Y	San Francisco Chronicle
6027	-0,51	3,33	Y	Bronco Roundup
6037	-1,07	4,45	Y	Los Angeles Times
6055	-0,78	2,12	Y	Napa Valley Register
6057	-1,43	0,25	Y	The Union
6061	-1,64	0,17	Y	Tahoe Daily Tribune
6073	-0,99	1,23	Y	KPBS
6079	-0,92	2,96	Y	The Tribune
6083	-0,66	1,56	Y	Santa Barbara Independent
6085	-1,20	1,64	Y	San Francisco Chronicle
6087	-0,37	4,19	Y	Santa Cruz Sentinel
6111	-0,90	0,27	N	–
15009	-1,27	1,88	Y	The Maui News
30049	-0,33	14,97	Y	Independent Record
49053	-0,81	0,83	Y	St. George News
53005	-0,41	0,87	Y	Tri-City Herald
53031	-0,78	1,99	Y	Peninsula Daily News
53071	-0,38	3,63	Y	KEPR

Notes: Own construction.