Analyzing the Effect of the 2017 Women's March on the 2018 Primary Elections

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Abstract

Since 2016 U.S. presidential election, there have been a number of large, well-coordinated protests across the United States. In 2017, people gathered in airports across the U.S. to rally against Executive Order 13769; in 2018, American students organized March for Our Lives in support of tighter gun control. Many people pour money and time into organizing these protests, but I wanted to understand: how much do these protests affect political change? I used the 2017 Women's March, a worldwide protest held on January 21, 2017 that advocated women's rights, to answer this question. I took an instrumental variable approach, using snowfall on the day of the march as an instrument for march attendance and investigated its effect on the proportion of women running for office and the success rate of women in the 2018 U.S. House primary race. First stage results showed that one inch of snowfall caused a 24.9% decrease in march attendance. IV estimates indicated that the effect of march attendance on political outcomes in the 2018 U.S. House primary races was a statistically significant and precise zero. However, the 2017 Women's March may still have had an effect on other political outcomes not measured in this study, or it may have had a larger national effect.

Introduction

Since the 2016 U.S. presidential election, the U.S. media have covered numerous high-profile political protests. Examples include protests organized against Executive Order 13769 in January 2017 and the March for Our Lives in support of tighter gun control in March 2018. Both time and effort are required to organize these large-scale rallies, and I wondered: can these protests create tangible political change? Specifically, I was interested in whether protests encourage certain populations to run for elected positions and whether these candidates are successful. To answer this question, I investigated the Women's March, a worldwide protest held on January 21, 2017 that advocated women's rights, in the context of its effects on the proportion of female candidates running for political office and the success rate of female candidates in the 2018 U.S. House primary race.

The 2017 Women's March provides a unique opportunity for analysis of protests and political change. First, the 2017 Women's March was the largest single-day protest in U.S. history. An estimated 3.3 to 4.6 million people participated across 680 locations in the U.S (Figure 1). Furthermore, it was a direct response to President Trump's administration and advocated politically liberal ideologies. Thus, it is plausible that the march affected political change, making it possible to test how the marches affected political outcomes (as measured by the proportion of female candidates running for political office and the success rate of female candidates during the 2018 U.S. House primary).

In an effort to avoid reverse causation, I used an instrumental variable approach. Specifically, I used a 2SLS regression of the proportion of female primary candidates and the success rate of female candidates in the 2018 U.S. House primary race on attendance at the 2017 Women's March instrumented by snowfall on a city-level. I initially hypothesized that larger crowds at the 2017 Women's March caused an increase in the proportion of female political candidates in the 2018 midterm primaries. However, I found that while the first stage estimates were adequate, the IV estimates indicated that attendance at the march had a statistically significant and precise zero effect on the number and proportion of women running, as well as winning, in the 2018 U.S. House primaries.

My study adds to a literature that investigates the political impact of protests. Many of these studies have used weather-related instruments to avoid endogeneity of regressors. Colins and Margo (2004, 2007) used rainfall as an instrument to study the effects of U.S. race-related riots in the 1960s on the value of black-owned property; they found that riots increased the racial gap in the value of property. Similarly, Madestam, Shoag, Veuger, and Yanagizawa-Drott (2013) exploited rainfall to calculate the effect of Tea Party rallies in 2009 on political outcomes. The results of their study indicated that the Tea Party rallies strengthened grassroots movements and pushed policymakers towards more conservative voting patterns.

While my study is inspired by Madestam *et al*. (2013), it is unique because it investigates a female-related movement in an age when online social networks may be as important as, if not more important than, human networks. The distinction between online social networks and networks formed through physical interaction is important because Madestam *et al*. (2013) suggested that the social connections formed during protests were integral to the strength of the Tea Party movement. I found zero effect of the 2017 Women's March on political outcomes, and I believe that part of the reason may be due to evolving technological capabilities that diminish the value of human connections formed through rallies.

The paper proceeds as follows. In Section 1, I describe the construction of my dataset and its strengths and weaknesses. In Section 2, I present my empirical methods. In Section 3, I cover the results of my empirical tests. Section 4 concludes and links my results back to the larger topic of protests and political impact.

Section 1: Data

My dataset contained 757 observations on the city level. Election data on the congressional district level or county level was disaggregated to the city level. The dataset was restricted to marches that occurred in cities within the 50 U.S. states (excluding the Virgin Islands and Puerto Rico) on January 21, 2017. Observations without attendance estimates or proper location labels (e.g. missing the state where the march took place) were excluded (Table I). Weaknesses of the dataset included limited observations, precision and limited available data. For example, many cities could not be matched to complete weather data. Additionally, attendance at the 2017 Women's March was estimated, especially for larger crowds, and could have resulted in measurement error. Moreover, crowd size measurement error could be correlated with snowfall. The potential correlation between measurement error and snowfall would increase the point estimate of the IV regression as the coefficient of the first stage decreases with measurement error, and crowd-size measurement error is eliminated in the reduced form regression. Ideally, I would have found an instrument that was uncorrelated with measurement error. However, due to time constraints, that was infeasible.

Attendance by city at the 2017 Women's March was recorded on a Google spreadsheet by Jeremy Pressman of the University of Connecticut and Erica Chenowith of the University of Denver. The raw data on attendance was first sourced from local policy, city or state officials, and march organizers at each location. If local sources were unavailable to provide attendance counts for a location, attendance was estimated by Pressman and Chenowith via photos. I used the "Best

Guess" estimates, which were produced using the following assumptions: (1) For cases where the high estimate is greater than 300 people: (a) adjust low estimate upward by 10%; (b) adjust high estimate downward by 10%; then (c) take the average of these adjusted values. (2) For cases where high estimate is 300 people or less, take the average of low estimate and high estimate (observers tend to produce more accurate head counts when there were 300 people or less). (3) For cases where high estimate and low estimate are equivalent, take this estimate as "true" (Pressman, Chenowith 2017).

Weather data was gathered from the National Oceanic and Atmospheric Administration's Global Historical Climatology Network Daily measurements. Measurements included precipitation, maximum temperature, minimum temperature, snowfall, and snow depth on January 21, 2017 by city.

Data on the 2018 primary candidates was sourced from FiveThirtyEight's "Patterns in open Democratic and Republican Primary Elections" dataset. The dataset included Republican and Democratic candidates in the 2018 primary elections who were not running against an incumbent candidate of their same party for the U.S. House, the U.S. Senate, and state governor. Given that state-level controls were used in this study, at-large primary races (U.S. Senate and state governor) were not of interest. Instead, this study focused on metrics from the U.S. House primary race. Variables to measure the proportion of women running in the U.S. House primaries were constructed by congressional district. Dummy variables were also constructed by congressional district to measure whether a woman had won the U.S. House primaries.

Demographic information was taken from the Census Bureau's American Community Survey 2012-2016 5-year Estimates. The 2012-2016 5-year Estimates were the most effective data source in this study because the dataset includes information on all towns and cities, regardless of population size. Some of the 2017 Women's Marches took place in smaller towns with populations of less than 65,000.

County-level voting data for the 2016 presidential election was scraped from Townhall.com. This data was used to control for political lean. Furthermore, it was used to check for exogeneity between attendance at the 2017 Women's March and political outcomes prior to 2017.

A dataset of names and genders was used to match the names of political candidates to gender. The data was sourced from the Social Security Administration.

Section 2: Empirical Methods

Using a simple regression to study the effect of political rallies on political outcomes is deceptive and problematic because the correlation between endogenous and exogenous variables is likely not causal. To remedy this, I used 2SLS and an instrument of snowfall to investigate how the size of the 2017 Women's March affected political outcomes in the 2018 primary election. In the first stage, the log of the best guess march attendance was regressed on snowfall on January 21, 2017 by city (Equation 1). Robustness was tested by using different measures of attendance (best guess, minimum estimate, maximum estimate).

$$\log(attendance)_{city} = \alpha_1 + \beta_1 * snow_{city} + \gamma_1 * Z_{city} + \epsilon_{1,city} \tag{1}$$

The independent variable of interest is "$snow$." The vector Z_{city} captures city-level population, disaggregated county-level 2016 presidential election results, weather controls on January 21, 2017, region, and state controls; $\epsilon_{1,city}$ is the city-level error term. Robust standard errors were reported.

The reduced form of the instrumental variable regression was achieved by regressing political outcomes in the 2018 primary elections on snowfall on January 21, 2017 by city (Equation 2). Primary election results were measured at the congressional district level, and the election results were matched to cities by the congressional district in which the city was located.

$$y_{city} = \alpha_2 + \beta_2 * snow_{city} + \gamma_2 * Z_{city} + \epsilon_{2,city} \tag{2}$$

y_{city} represents the proportion of female candidates or the success rate of female candidates in the U.S. House midterm primaries. The main variable of interest is again "$snow$," which is an instrument for march attendance. Z_{city} is defined as above. The term $\epsilon_{2,city}$ is the city-level error term; robust standard errors were reported.

Equation 3 presents the structural equation, which measures the effect of attendance at the Women's March on the 2018 primaries. Additionally, 2016 presidential election results were regressed on march attendance to check for exogeneity between attendance at the 2017 Women's March and political outcomes prior to the march. If the weather instrument satisfies exclusion restriction (i.e. it truly only affects political change through the number of protesters at the Women's March), then there is a causal interpretation to the 2SLS regression.

$$y_{city} = \alpha_2 + \beta_3 * \log(attendance)_{city} + \epsilon_{3,city} \tag{3}$$

Exclusion restriction was likely not satisfied; for example, snowfall could have also affected media coverage of the march, which could have in turn affected the strength of the movement and political change. Given the time limitations of this study, it was impractical to collect data to control for media coverage. Yet both media coverage and march attendance serve to measure the variable of interest, i.e. the strength of the movement.

Given the instrumental variable approach, one of the main assumptions of this study was that the snowfall experienced on January 21, 2017 was random. Ideally, the probability of snowfall would have been used to control for locations that regularly get more snowfall than other locations. With limited time and data, proxies for the probability of snowfall were used. Specifically, temperature, snow depth (not including snowfall on January 21, 2017), rainfall, and state-level controls were used to control for typical weather conditions expected in January for each city.

Section 3: Results

First Stage: The Effect of Snowfall on March Attendance

Table II summarizes the results of the estimation from Equation 1. All regressions include weather controls (precipitation, maximum temperature, snow depth), region fixed-effect, and state fixed-effect controls. Snowfall caused a statistically significant decrease in the log of march attendance at the $p<0.1$ level; an extra inch of snowfall caused a 24.9% decrease in march attendance. However, the estimate was sensitive to the standardization of march attendance; regressing the best guess of turnout per capita or the best guess value of attendance resulted in negative but statistically insignificant estimates. Thus, the results from the first stage were adequate but not robust.

As an additional check of robustness, the first stage regression was repeated using the minimum and maximum estimates for attendance (Table III). The results are similar when to those obtained when using the best guess estimate; snowfall is statistically significantly correlated with a decrease in the log of march attendance (minimum and maximum) at the $p<0.01$ level. An extra inch of snowfall caused a 27% and 27.9% decrease in march attendance when regressing the log of the minimum and maximum attendance, respectively. The estimates of the effect of snowfall on march attendance provided in columns (2), (3), (5), and (6) were negative but statistically insignificant.

Furthermore, the exogeneity of the 2017 Women's March and political outcomes prior to the march was tested, and the results are presented in Table IV. The estimates were obtained by running the regression in Equation 2, using 2016 presidential election results as the exogenous variable. Controls were added in column by column, and none of the coefficients on march attendance instrumented by snow were significant. Thus, the data passes the test for exogeneity, and we can conclude that the 2017 Women's March had no bearing on political outcomes that had already occurred.

Reduced Form/Structural Equation: The Effect of March Attendance on Political Outcomes

The results of the reduced form are summarized in Table V. There were five 2018 U.S. House primary political outcomes of interest: (1) the number of female Democratic candidates, (2) the number of female Republican candidates, (3) the proportion of female candidates in the House race, (4) the rate at which a female wins the primary election for the Democratic primary race, and (5) the rate at which a female wins the primary election for the Republican primary.

To measure the effect of march attendance on political outcomes, 2SLS regressions were run using Equation 3 and the five specified political outcomes of interest, by city of march (Table VI). For each outcome variable of interest, I found that march attendance as instrumented by snowfall had no statistically significant effect on the outcome. Given the magnitude of the estimates, the standard errors, and the linear-log model, the constants can be interpreted as a significant and precise zero. For instance, the largest estimate was 0.3 (SE: 0.195) for the regression of the number of female Democratic U.S. House candidates on march attendance. Because march attendance was measured on a log scale, the largest estimate of 0.3 signals that a 1% increase in march attendance caused anywhere from a 0.0009 decrease to a 0.0069 increase (95% confidence interval) in the number of female Democratic U.S. House candidates. In addition, if the march has heterogeneous effects on different groups of people, the IV estimates measure the Local Average Treatment Effect (LATE), and are biased away from zero. Thus, these estimates may be interpreted as significant and precise zeros, and it can be concluded that the Women's March had no effect on the number or proportion of females running, or female candidate success rate in the 2018 U.S. House primary race.

While there was no effect of the Women's March on the proportion of women running and succeeding in 2018 primary elections, this result does not imply that the Women's March had no political effect at all. There are many other exogenous variables that may have been affected – for instance, the voter turnout by gender or political outcomes of more local elections (e.g. city council, school board). The effects of the march may also be slow to arise, in which case one might see the Women's March affect future political outcomes.

Furthermore, my regression assumes that the effects of protests are local; that is, local protests will affect local political outcomes. However, many people did not physically attend a Women's March and instead watched coverage of the protest on TV or followed the protest live via social media. As a result, the protests may have had a national effect, rather than the local effect traditionally associated with protests. One way to investigate this further is to perform an event study on the national level and test any discontinuity in political outcomes before and after the 2017 Women's March.

Section 4: Conclusion

Protests and rallies have become popular forms of expression in the current political climate. While protests have been widespread and frequent, it is unclear whether they truly have an effect on political outcomes. In my study, I used the 2017 Women's March to investigate the role of protests in the 2018 primary elections via an instrumental variable approach. While there was a statistically significant first stage, march attendance had no statistically significant effect on the number of women running for office or the success rate of the women running for office in the U.S. House primary election.

Although my results point to a precise and significant zero effect, there are limitations to my study. The analysis is restricted to states in which at least one city that held a Women's March experienced snowfall on January 21, 2017. To analyze the effect of the Women's March in warmer areas that do not experience snowfall, an instrument other than snowfall is required. Precipitation may be a viable substitute, but the quality of the dataset must be improved so that the first stage is strong enough to use an instrumental variable approach. Further, this study investigated limited political outcomes by focusing on the local effects of the Women's March. Future studies may consider other local political outcomes potentially affected by the Women's March or investigate the national effect of the 2017 Women's March.

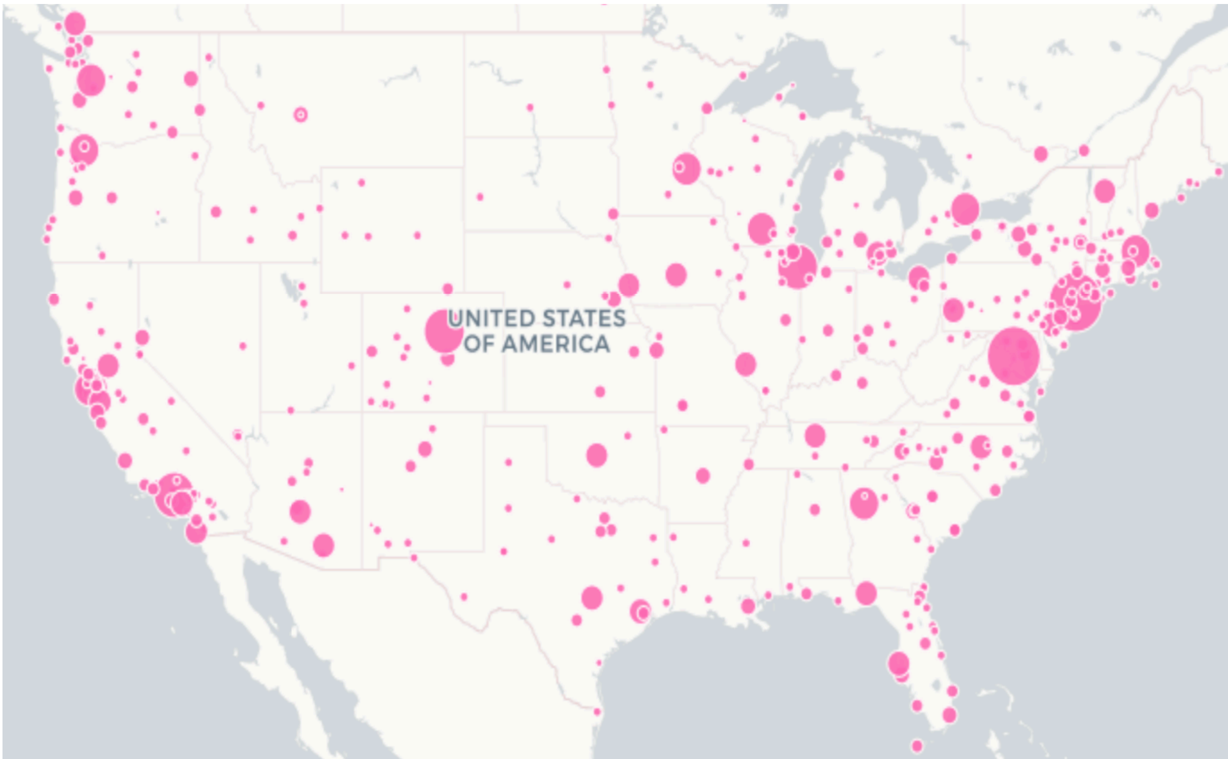

Figure 1. Map of the locations of the 2017 Women's Marches across the United States. Size of the dot indicates the relative size of the march (measured by attendance). Map created by Eric Compas on Carto (https://geographer.carto.com/viz/a229d5d2-e04a-11e6-9c98-0e98b61680bf/embed_map). Dataset used to generate the map was the same as the dataset used in this study before restrictions (e.g. restricted to 50 U.S. states) were applied.

Table I. *City-level Summary Statistics*

	Mean	SD	Min	Max	Observations
Log(attendance)	5.65	2.56	0.00	12.73	757
Log(population)	10.39	2.20	4.25	15.95	727
Snow (inches)	0.16	1.06	0.00	13.20	757
Frac of votes for Hillary Clinton in 2016 presidential election	0.48	0.15	0.14	0.89	753
Frac of votes for Donald Trump in 2016 presidential election	0.46	0.15	0.08	0.84	753
Frac of Democratic female candidates in 2018 U.S. House primary election	0.36	0.32	0	1	462
Frac of Republican female candidates in 2018 U.S. House primary election	0.16	0.30	0	1	381
Dummy: 1 if female candidate won U.S. House Democratic primary	0.47	0.50	0	2	419
Dummy: 1 if female candidate won U.S. House Republican primary	0.19	0.39	0	1	338
Frac of Democratic female candidates in 2018 Governor and U.S. Senate primary election	0.28	0.28	0	1	380
Frac of Republican female candidates in 2018 Governor and U.S. Senate primary election	0.17	0.18	0	0.67	628
Dummy: 1 if female candidate won Governor and U.S. Senate Democratic primary	0.39	0.49	0	1	267
Dummy: 1 if female candidate won Governor and U.S. Senate Republican primary	0.40	0.49	0	1	454

Note: 757 city-level observations. Observations were restricted to marches that occured in cities within the 50 U.S. states (excluding the Virgin Islands and Puerto Rico) on January 21, 2017. Observations without attendance estimates or proper location lables (e.g. missing the state where the march took place) were excluded. Election data was disaggregated from either the county level or congressional district level. Missing election values indicate that there was not a relevant race from which to construct the variable.

Table II. *The Effect of Snow on Attendance at the 2017 Women's March*

	(1)	(2)	(3)
	log(best guess)	best guess: turnout per capita	best guess
snow	-0.249**	-0.00481	-1402.9
	(0.0885)	(0.00300)	(1685.0)
tmax	0.0407*	0.00185*	-179.3
	(0.0191)	(0.000861)	(287.0)
precip	0.773	0.0325	1747.9
	(0.836)	(0.0206)	(7207.9)
snowdepth	0.0282*	0.00103	255.2
	(0.0117)	(0.000555)	(240.7)
log(population)	0.837***	-0.0128*	7175.5***
	(0.0927)	(0.00537)	(1661.1)
% demvotes2016	8.174	0.0235	168584.7*
	(4.469)	(0.153)	(82246.8)
% gopvotes2016	5.808	-0.103	109187.9
	(4.564)	(0.161)	(80080.1)
% diff(dem-gop)2016	-0.840	-0.0276	60745.4**
	(0.693)	(0.0259)	(20630.9)
Region controls?	Y	Y	Y
State controls?	Y	Y	Y
N	207	207	207
R^2	0.766	0.771	0.603

Note: Analysis was done on the city level. Snowfall was measured in inches on January 21, 2017. All regressions included weather (precipitation, maximum temperature, snow depth), 2016 election, population, region fixed-effect, and state fixed-effect controls. Each column regresses a different standardization of the best guess of attendance. Column (1) regresses the log of the best guess, column (2) the best guess of turnout per capita, and column (3) the best guess. Snowfall is statistically significantly correlated with a decrease in the log of march attendance; an extra inch of snowfall caused a 24.9% decrease in march attendance. The estimates of the effect of snowfall on march attendance provided in columns (2) and (3) were negative but statistically insignificant. Robust standard errors in parentheses.

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

Table III. *Robustness of the Effect of Snow on Attendance at the 2017 Women's March*

	(1)	(2)	(3)	(4)	(5)	(6)
	log_attend_min	perc_attend_min	attend_min	log_attend_max	perc_attend_max	attend_max
snow	-0.270**	-0.00556	-1308.7	-0.279**	-0.0105	-3117.4
	(0.0979)	(0.00443)	(2698.7)	(0.100)	(0.00653)	(3744.4)
tmax	0.0485*	0.00331	-305.3	0.0423*	0.00398*	-398.6
	(0.0206)	(0.00170)	(466.0)	(0.0199)	(0.00193)	(637.8)
precip	1.051	0.0651	1756.1	0.819	0.0704	3881.6
	(0.877)	(0.0437)	(12151.3)	(0.877)	(0.0453)	(16020.7)
snowdepth	0.0275	0.00152	511.4	0.0290*	0.00217	567.1
	(0.0144)	(0.00113)	(377.4)	(0.0123)	(0.00122)	(534.8)
log(pop)	0.843***	-0.0244*	11884.1***	0.859***	-0.0266*	15947.3***
	(0.0969)	(0.0113)	(2797.8)	(0.0960)	(0.0116)	(3691.2)
% demvotes2016	9.355	0.0375	305989.7*	8.042	0.0182	374679.2*
	(5.039)	(0.259)	(141157.7)	(4.754)	(0.333)	(182772.9)
% gopvotes2016	6.992	-0.177	195439.9	5.657	-0.261	242679.4
	(5.111)	(0.273)	(137195.1)	(4.835)	(0.352)	(177955.6)
% diff(dem-gop)2016	-0.674	-0.0352	118059.2**	-0.871	-0.0630	134991.3**
	(0.743)	(0.0505)	(35911.9)	(0.716)	(0.0571)	(45844.8)
Region controls?	Y	Y	Y	Y	Y	Y
State controls?	Y	Y	Y	Y	Y	Y
N	207	207	207	207	207	207
R^2	0.744	0.706	0.633	0.760	0.781	0.603

Note: Analysis was done on the city level. Snowfall was measured in inches on January 21, 2017. All regressions included weather (precipitation, maximum temperature, snow depth), 2016 election, population, region fixed-effect, and state fixed-effect controls. Each column regresses a different standardization of the best guess of attendance. Columns (1) and (4) regress the log of the minimum and maximum estimates, respectively; columns (2) and (5) the minimum and maximum turnout per capita, respectively; and columns (3) and (6) the minimum and maximum estimates, respectively. Snowfall is statistically significantly correlated with a decrease in the log of march attendance (minimum and maximum) at the p<0.01 level. An extra inch of snowfall caused a 27% and 27.9% decrease in march attendance when regressing the log of the minimum and maximum attendance, respectively. The estimates of the effect of snowfall on march attendance provided in columns (2), (3), (5), and (6) were negative but statistically insignificant. Robust standard errors in parentheses.

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

Table IV. *Exogeneity of 2017 Women's March and 2016 Political Outcomes*

	(1)	(2)	(3)
	log_total_votes16	log_votes_dem16	log_votes_gop16
log(bestguess)	0.185	0.0875	0.180
	(0.311)	(0.350)	(0.286)
tmax	-0.0109	-0.00490	-0.0110
	(0.0176)	(0.0185)	(0.0193)
precip	-0.932**	-0.943*	-0.840*
	(0.308)	(0.377)	(0.341)
snowdepth	-0.00318	-0.00163	-0.00922
	(0.0101)	(0.0107)	(0.0113)
log(population)	0.401	0.543	0.322
	(0.277)	(0.310)	(0.253)
Region controls?	Y	Y	Y
State controls?	Y	Y	Y
N	207	207	207
R^2	0.798	0.844	0.760

Note: Analysis was done on the city level. All regressions included weather (precipitation, maximum temperature, snow depth), population, region fixed-effect, and state fixed-effect controls. Estimates are the from the 2SLS instrumental variable regression specified by Equation 2, where the exogenous variables were the log of total votes (column (1)), the log of votes for the 2016 Democratic presidential candidate (column (2)), and the log of votes for the 2016 Republican presidential candidate (column (3)) in the general election. None of the estimates are statistically significant, supporting the exogeneity of the 2017 Women's March from political outcomes prior. Robust standard errors in parentheses.

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

Table V. *Reduced Form Estimates for 2018 U.S. House Primary Race*

	(1)	(2)	(3)	(4)	(5)
	# female dem cand	# female gop cand	proportion of female cand	rate of female win: dem primary	Rate of female win: gop primary
snow	-0.0745	0.0182	-0.0271	-0.0374	-0.000225
	(0.0490)	(0.0322)	(0.0141)	(0.0327)	(0.0250)
tmax	-0.0143	-0.00284	-0.00475	-0.00739	-0.00228
	(0.0120)	(0.00385)	(0.00364)	(0.00717)	(0.0111)
precip	0.729^{**}	0.0829	0.359^{*}	0.508^{*}	-0.114
	(0.272)	(0.179)	(0.151)	(0.199)	(0.587)
snowdepth	0.00841	0.00179	0.00187	0.00444	0.00531
	(0.00755)	(0.00316)	(0.00210)	(0.00460)	(0.0191)
log(population)	-0.0426	0.0317^{*}	0.0128	0.0274	0.0729
	(0.0465)	(0.0152)	(0.0149)	(0.0257)	(0.0478)
% demvotes2016	-1.421	0.622	1.254	0.638	-1.840
	(2.456)	(0.941)	(1.143)	(1.743)	(6.479)
% gopvotes2016	-0.398	0.183	1.448	0.544	-2.173
	(2.689)	(1.000)	(1.158)	(1.841)	(6.506)
% diff(dem-gop)2016	-0.635	0.0746	0.154	-0.0252	0.0376
	(0.493)	(0.179)	(0.164)	(0.302)	(0.551)
Region controls?	Y	Y	Y	Y	Y
State controls?	Y	Y	Y	Y	Y
N	207	207	207	134	73
R^2	0.424	0.575	0.438	0.578	0.671

Note: Analysis was done on the city level. Snowfall was measured in inches on January 21, 2017. All regressions included weather (precipitation, maximum temperature, snow depth), 2016 election, population, region fixed-effect, and state fixed-effect controls. Each column regresses a political outcome in the 2018 U.S. House primary race on snowfall on the date of the 2017 Women's March. Columns (1) and (2) regress the number of female Democratic and Republican candidates, respectively; (3) the proportion of female candidates in the House; (4) and (5) the rate at which a female wins the primary election for the Democratic and Republican primaries, respectively. Robust standard errors in parentheses.

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

Table VI. *IV Estimates for 2018 U.S. House Primary Race*

	(1)	(2)	(3)	(4)	(5)
	# female dem cand	# female gop cand	proportion of female cand	rate of female win: dem primary	Rate of female win: gop primary
log(bestguess)	0.300	-0.0734	0.109	0.280	0.000290
	(0.195)	(0.115)	(0.0637)	(0.247)	(0.0225)
tmax	-0.0265	0.000143	-0.00918	-0.0168	-0.00228
	(0.0168)	(0.00497)	(0.00485)	(0.0129)	(0.00770)
precip	0.497	0.140	0.275^{**}	0.344	-0.114
	(0.301)	(0.194)	(0.0970)	(0.214)	(0.418)
snowdepth	-0.0000440	0.00386	-0.00120	-0.000402	0.00527
	(0.00790)	(0.00372)	(0.00270)	(0.00558)	(0.0122)
log(population)	-0.293	0.0931	-0.0784	-0.165	0.0726^{*}
	(0.152)	(0.0963)	(0.0502)	(0.155)	(0.0335)
% demvotes2016	-3.871	1.222	0.363	-2.129	-1.824
	(2.818)	(1.410)	(1.080)	(2.639)	(4.580)
% gopvotes2016	-2.139	0.609	0.815	-2.149	-2.155
	(2.727)	(1.214)	(1.046)	(2.555)	(4.574)
% diff(dem-gop)2016	-0.383	0.0129	0.246	0.729	0.0384
	(0.463)	(0.199)	(0.162)	(0.663)	(0.367)
Region controls?	Y	Y	Y	Y	Y
State controls?	Y	Y	Y	Y	Y
N	207	207	207	134	73
R^2	0.280	0.532	0.237	0.005	0.671

Note: Analysis was done on the city level. The log of the best guess estimate for attendance was instrumented for by snowfall. All regressions included weather (precipitation, maximum temperature, snow depth), 2016 election, population, region fixed-effect, and state fixed-effect controls. Each column regresses a political outcome in the 2018 U.S. House primary race on the log of the best guess estimate for attendance at the 2017 Women's March. Columns (1) and (2) regress the number of female Democratic and Republican candidates, respectively; (3) the proportion of female candidates in the House; (4) and (5) the rate at which a female wins the primary election for the Democratic and Republican primaries, respectively. The log of the best guess attendance had no statistically significant effect on any of the outcome variables. Robust standard errors in parentheses.

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