# Did the Women's March Work? Re-Evaluating the Political Efficacy of Protest

JONATHAN PINCKNEY Norwegian U. of Science and Technology (NTNU)

**v** he Women's March on Washington and its over 600 "sister marches" were likely the single largest day of protest in American history, and were followed by a wave of political organizing that re-invigorated progressive politics after the 2016 election of President Donald Trump. Yet to what degree can we attribute the emergence of this Anti-Trump "Resistance" to the Women's Marches themselves? Do public protests such as the Women's March truly change political outcomes or do they simply reflect underlying public opinion? There is a growing literature arguing that protest has important effects independent of its endogenous relationship to public opinion. In this paper, I test this argument on the scale of the Women's March. I instrument Women's March participation using rainfall data from the day of the march and measure the effects of instrumented march size on three dependent variables: the creation of "Indivisible" groups, shifts in voting by congressional representatives, and the shift towards Democratic congressional candidates in the 2018 elections. I find that the instrumented size of Women's March protests significantly increased the Democratic vote share in the 2018 election. These findings provide strong evidence that the Women's Marches were a significant transformative event in American politics, with real political consequences, and speak to the power of peaceful protest as a social movement tactic.

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Jonathan Pinckney is a Post-Doctoral Research Fellow, Department of Sociology and Political Science, NTNU

(jonathan.pinckney@ntnu.no

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# INTRODUCTION

he Women's March of January 21st, 2017 is one of the most prominent examples of public protest in recent American history, and was the "trigger" for a massive outpouring of social dissent that became known as "The Resistance." (Meyer and Tarrow 2018). The size of the protests was nearly unprecedented, and a significant deviation from the norm of protests in the United States in the recent past. Women's March events averaged nearly 7,000 participants (Chenoweth and Pressman 2017). For comparison, a representative sample of protests in the United States in the recent past found protest events in the United States had a mean participation of 61 participants. The average turnout was also more than six times higher than the April 15, 2009 Tax Day protests, which jumpstarted the Tea Party movement (Beyerlein et al. 2018).

In the immediate aftermath of the protests, Democratic activists claimed that the marches indicated widespread disapproval of President Trump's policies, and could spark a movements against him. Columnist Eugene Robinson observed: "The millions who participated nationwide now constitute the kind of broad-based network that can be harnessed into effective political action" (Robinson 2017). In the 2018 mid-term elections, the first chance for the national electorate to weigh in on the Trump presidency, the Democratic party experienced significant gains - winning the popular vote by more than seven percent and capturing control of the House of Representatives. Many took the Democratic shift as indicative in part of the power of the Resistance to achieve political change, and contrasted it with earlier more diffuse movements such as the "Occupy Wall Street" movement, that mobilized large numbers of people but failed to lead to major political changes.

Yet disentangling the effects of protest is inherently challenging. To what degree did the Women's Marches effect political change and to what degree were they simply indicative of a deeper shift in public opinion in the country (or simply symptomatic of increasing partisan polarization). Does political protest actually work? And if so, how? The social movements literature gives us conflicting answers on the potential effectiveness of protest, while the nonviolent resistance literature suggests that peaceful protest can be effective, but typically measures only highly aggregated outcomes and does not adequately address questions of endogeneity and reverse causality.

In this paper I address this question. I look at the effect of the Women's Marches on three key areas:

movement building, as measured by the creation and size of "Indivisible" groups; policymaking, as measured by shifts in legislator DW-NOMINATE scores, and electoral outcomes, as measured by the shift in Democratic party vote share in 2018. I address the endogeneity of protest size to underlying political dynamics through an instrumental variable analysis. I instrument the size of participation in the 2017 Women's March with a plausibly exogenous instrumental variable: the weather on the date on the marches. I show first that weather significantly predicts decreased turnout, and is thus a reliable instrument for predicting protest size that has no plausible alternative path to affecting my dependent variables. I show secondly that, when instrumented using good weather, large protests on the day of the original Women's March predicts significantly increased movement activity, left-ward shifts in congressional voting scores, and a greater swing to the Democrats in the 2018 midterm elections.

The paper has important implications for our understanding of the power of protest to bring about political change, and the mechanisms through which that change occurs. I argue, following Madestam and his co-authors 2013 that the power of protest comes primarily not from its ability to signal discontent to elites, but rather with the effects of protest on the protesters themselves. Participation in major protest events such as the 2017 Women's March socialized protest participants towards greater left-wing attitudes, helped jump-start local organizing efforts, and socialized the participants to greater political participation. These combined effects helped cement the growth of the anti-Trump "Resistance" leading to significant gains for liberal politics in the United States.

The paper proceeds as follows. In section 2 I discuss what we know so far about the political effectiveness of protest. In section 3 I discuss the origin and dynamics of the 2017 Women's March. In section 4 I introduce my research design, including the use of good weather as an instrument for protest size. In section 5 I present and discuss my findings. Section 6 concludes.

# THE POWER OF PROTEST

# **Existing Literature**

The effectiveness of protest is a core question for the study of extra-institutional politics. Social movements' scholars have long wrestled with the ways in which challengers from outside the polity

can challenge those within (Tilly 1978; Tarrow 1998).<sup>1</sup> Some scholars conclude that social movements do have a strong impact on political outcomes (Baumgartner and Mahoney 2005; Piven 2006). For example, Htun and Weldon (2012) find that feminist social movements are the key factor driving advancement in violent against women policies. Yet others find little or no influence (Soule et al. 1999; Giugni 2007). For instance, McAdam and Su (2002) find that the US anti-war movement in the 1960s had difficulty pressuring elites while also shifting public opinion. Branton et al. (2015) find that exposure to immigration protests shifted public opinion in favor of the protesters, but that this effect was limited to immigrants.

A more singularly optimistic tone comes from the literature on nonviolent resistance. Early work from Sharp (1973) and Ackerman and Kruegler (1994) suggested that nonviolent resistance movements, when skillfully employing tools of strategy and nonviolent discipline could bring about major political transformations, even in the most unfavorable circumstances. Schock (2005) pointed to a similar dynamic, arguing that so-called "unarmed insurrections" could oust dictatorships if they could successfully foster points of leverage over those opposing regimes and deploy a dynamic micture of tactics of concentration and dispersion. Building on this work, Chenoweth and Stephan (2011) show that nonviolent resistance campaigns seeking "maximalist" goals of regime change, secession, or an end to a military occupation succeeded in achieving their goals in roughly 50% of cases from 1900 to 2006.

Scholars are divided on the mechanisms whereby protest might affect political outcomes. McAdam and Su (2002) identify three mechanisms: *disruptive protest, signaling* and *public opinion shift*. Chenoweth and Stephan (2011) emphasize the importance of participation, and how large, diverse participation in protest campaigns can lead to both greater tactical innovation and more points of connection with those in power, leading to greater opportunities to undermine "pillars of support" (Helvey 2004). Similarly, Uba (2005) finds that the size and degree of disruption of anti-privatization protests in India significantly slowed the pace of privatization.

In a classic treatment of the subject, Lohmann (1993) argues that protest acts as a signal to political

<sup>&</sup>lt;sup>1</sup>For an excellent summary of major research efforts on the effectiveness and long-term outcomes of social movements, see Amenta et al. (2010)

elites of underlying shifts in public opinion. Size is a clear indicator of the strength of this signal, with larger protests acting as stronger signals that the underlying demands of the protest are widely shared.<sup>2</sup>

Protest may also lead to political change through the effects that it has on its participants. Participation in protest tends to lead to more political participation in the future, as well as socialization into the attitudes of the protest group (Opp and Kittel 2010). Protest participants have a powerful experience and potentially a new social network on which to draw while they engage in future political action. This level of organization and socialization can then lead to greater pressure on elected officials.

Finally, protest can affect political outcomes by imposing direct economic costs on its opponents. Labor strikes and other methods of noncooperation are the most prominent form of action that rely on this mechanism. I expect that public demonstrations such as the Women's March would be unlikely to operate through this mechanism. Peaceful public demonstrations are often intentionally designed to not disrupt economic activity. The Women's Marches were no exception, with close cooperation with police and attempts to minimize the economic disruption of the event. Events with high turnout may even have boosted economic activity in their surrounding environment.

#### Challenges to Inference

Both the social movements literature and the nonviolent resistance literature have tended to focus on larger movements or campaigns, and given less attention to the disaggregated impact of particular protest events. Even most analyses based on protest events data tend to aggregate events to protest counts temporally or geographically. For example, McAdam and Su (2002) look at the count of various types of protest events aggregated to the national level. Walgrave and Vliegenthart (2012) aggregate all demonstrations on a particular issue area in Belgium when looking at agenda-setting effects of protest. Gillion (2012) disaggregates protests in the United States by congressional district, but aggregates them temporally to an annual level, and Banaszak and Ondercin (2016) aggregate protests on women's movement issues across the United States by quarter.

This tendency towards aggregation makes it difficult to tease out the causal relationships between  $^{2}$ In an experimental study of the effects of protest on policymakers, Wouters and Walgrave (2017) find that numbers and agreement within the protest group are the most persuasive features of a protest for policymakers

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tactics and political outcomes. We have strong evidence that nonviolent resistance can work, and that social movements may, dependent on the political opportunity structure, and availability of resonant frames, lead to significant political change. Yet it is difficult to say exactly why, since our independent variables are measured at such a high level of aggregation. We know a lot about movements, but less about specific protests in particular locations.

In addition to the aggregation problem, most studies of protest face a fundamental endogeneity problem that is often ignored or only partially addressed. The occurrence and intensity of protest are unlikely to indicate a fully exogenous shock to the system but rather part of an ongoing process of political contention. Many of the observable correlates of protest and political effectiveness overlap. Insofar as these correlates can be measured, this issue can be remedied through the inclusion of appropriate control variables. However, many of the factors that plausibly influence both protest and political outcomes are not so easily observed. Thus, correlations between protest and political shifts in the direction of the protesters are empirically suspect.

Recent work has begun to address these challenges, but leaves many questions unanswered. Biggs and Andrews (2015) find that lunch counter sit-ins made desegregation significantly more likely in cities across the American South in 1960, controlling for several determinants of protest. Yet their measure of protest is a simple binary variable that does not allow for disaggregation in terms of size or intensity of protest.

Madestam et al. (2013) show that protest size on Tax Day, 2009, which they instrument using rainfall, significantly predicts several indicators of movement success for the Tea Party. Counties with large Tea Party protests saw large follow-up groups, more donations to major right-wing PACs, and a swing toward the Republicans in the 2010 mid-term elections. Their strategy addresses many of the methodological challenges of determining the impact of individual protest events, but the limited scale of the Tea Party tells us little about protest more broadly.

Omar Wasow (2017) examines the attributes of effective protest in more detail with an examination of the civil rights movement in the 1960s. Wasow shows that peaceful protests significantly increased public attention to the issue of civil rights, and that counties within 100 miles of a peaceful protest had major shifts towards the Democratic party in the 1968 presidential election, while counties within

100 miles of violent riots in the aftermath of the assassination of Dr. Martin Luther King, Jr. had significant shifts towards the Republicans. Simulating the 1968 election with and without peaceful and violent protests, Wasow argues there is good reason to believe that the post-assassination riots played a crucial role in giving an election victory to Richard Nixon. Yet Wasow does not include any measures of protest intensity to distinguish between the effects of small protests and large protests.

In this paper, I build on the insights from these early papers looking at the impact of specific protest events through examining one of the most recent major protest events: the 2017 Women's March on Washington and its associated "sister protests."

The Women's March provides an ideal environment in which to evaluate the power of protest. First, the march was an extreme outlier in American protest politics, both in size and dispersion. Thus, it provides a strong "best-case scenario" test of the power of protest. If protest can be effective, the Women's March protests should be effective. If the Women's March failed to have a significant political impact, it provides strong evidence for the skeptics of the power of protest. Second, the large number of events taking place on the same day provides an ideal environment for a natural experiment. Some localities experienced the "treatment" of a Women's March on January 21, 2017, and others did not. Once I have addressed the endogenous aspects of generating the protest itself (which I discuss below in section 4), this simultaneous shock provides strong grounds for causal inference.

What effects should we expect based on the character of the Women's March? I answer this by examining the precipitating causes of the march and its immediate aftermath.

# THE 2017 WOMEN'S MARCH

Planning for a "Million Woman March" on Washington to protect women's rights began immediately following the 2016 election of US President Donald Trump. Teresa Shook, a retired lawyer from Hawaii, created a Facebook group planning an event after discussions on the pro-Hillary Clinton Facebook Group "Pantsuit Nation." The event, publicized in the midst of the beginning of a wave of protest against Trump's election, grew rapidly, with over 10,000 people saying they would participate in the first 24 hours and over 100,000 soon afterwards (Stein 2017).

While the march began with little organizational backing, it grew quickly thanks to assistance from

several different "organizational tributaries" (Berry and Chenoweth 2018). The eventual "Women's March on Washington" had an organization behind it, and over 400 co-sponsors from several different strains of the American left.

In addition to the primary event in Washington, DC, however, over 600 "sister marches" were organized across the United States and indeed around the world. A comprehensive tally of events from the day of the Women's March includes everything from the estimated 1,600,000 who attended the three largest marches in DC, New York, and Los Angeles, to ten brave souls in the tiny town of Adak, Alaska, a village on a remote Aleutian island that has the distinction of being the Westernmost municipality in the United States.

The march was not explicitly partisan, and the organizers went to some lengths to ensure that their organization was not seen as simply an arm of the Democratic party. However, the causes around which march participants organized were overwhelmingly on the left of the American political spectrum (Fisher et al. 2017).

The marches were also highly geographically dispersed. While the largest events took place in major left-leaning urban centers, marches took place across the country, in small relatively rural areas and in purple and red states as well as blue states. In a study of a representative sample of Women's Marches, McKane and McCammon (2018) found that marches were most likely to occur in Democratic cities in predominately Republican states, and in places with a large existing social movement organization infrastructure, however, the effects of these variables are fairly small, indicating just how widespread the marches were. The marches also varied significantly in terms of their levels of attendance. Beyerlein and his co-authors 2018 estimate that while the largest protest had roughly 750,000 to a million attendees, the average was roughly 7,000, and around a quarter of events had fewer than 100 participants.

Anecdotally, the Women's Marches played a significant role in jump-starting the anti-Trump opposition. They were the first in a series of semi-regular major protest marches around various themes that took place during the first two years of the Trump presidency. Major protests took place at American airports in support of Muslim refugees after the issuing of the first "Muslim ban," and included the "March for Science," the "People's Climate March" and widespread marches focused on

healthcare during the summer of 2017 when the Republican-led congress was attempting to repeal the Affordable Care Act. The Women's March itself has become an annual tradition, with widespread demonstrations on the anniversary in 2018 and 2019. While the numbers in these follow-up marches have not matched the overwhelming numbers in the initial 2017 protest, they have remained some of the largest days of protest in American history. For instance, the 2019 Women's March, while largely described in the media as a failure due to divisions in the Women's March organization and accusations of anti-Semitism among the leadership of the Women's March organization, actually had more participants than the 2009 "Tax Day" protests that initiated the Tea Party movement (Chenoweth and Pressman 2019).

The impact of the Women's March on the subsequent anti-Trump "Resistance" can be seen clearly in the demographic characteristics of the resistance. As Putnam and Skocpol (2018) identify, the resistance is a movement that tends to be dominated not by the traditional "activist class" of the young, highly-educated, and urban. Instead, the movement has been spearheaded by local groups of predominately middle-aged educated white women in the suburbs, similar to the dominant demographics of the Women's March identified by Fisher et al. (2017).

Unlike prior progressive movements such as "Occupy Wall Street," the anti-Trump resistance has been focused on electoral change from the outset. As Putnam and Skocpol (2018) report: "Many of the local groups whose emergence was linked to Indivisible and the March a year ago are already ten months into an electoral 'turn.' They have one election cycle under their belt and concrete targets in their sights for 2018, 2019, and 2020."

# Hypotheses on Women's March Effects

One key benefit of large protests is as mobilizing moments for building larger movement infrastructures. Effective protests should not simply remain on the streets but instead turn into long-term organizing for future events. Thus, if the Women's March was effective, we should see it translating into more grassroots organization in the aftermath of the event. Since the Women's March was closely associated with the anti-Trump "Resistance" movement, if the march was effective in movement-building we should expect to see more movement-related activities in locations where large Women's Marches occurred.

 $H_1$ : Counties with large 2017 "Women's Marches" will have more "Resistance" activities than those without such marches.

While most Resistance groups do not explicitly identify themselves as members of the Democratic party, and encourage membership from Independents and Republicans, the substance of their agenda tends to be quite closely associated with a progressive agenda. Resistance groups have also been directly involved in recruiting Democratic candidates to run for office, interfacing with local Democratic party infrastructures. Thus, the first outcome that I measure is whether the Women's March impacted the Democratic Party's vote share in the 2018 election.

*H*<sub>2</sub>: Counties with large 2017 "Women's Marches" will have larger 2018 Democratic vote shares, *ceteris paribus*.

One key metric for the effectiveness of protest is whether policy changes are enacted in line with the preferences of the protesters. Participants in the Women's March did not speak with a single voice, or focus on a single issue. However, the issues motivating the majority of the participants to attend tend to be associated with more left-wing politics in the United States. In a random sample of participants in the Women's March Fisher et al. (2017, 2) found that the top five reasons participants gave for attending the Women's March were Women's Rights, Equality, Reproductive Rights, the Environment, and Social Welfare. If the Women's March was effective in motivating changes in policymaker behavior, we should expect to see elected officials voting in a stronger left-leaning direction.

*H*<sub>3</sub>: Representatives from districts with large 2017 "Women's Marches" will vote more left-wing than those without such marches, *ceteris paribus*.

# **RESEARCH DESIGN**

#### **Independent Variables**

My primary independent variables are the occurrence and size of a women's march on January 21, 2017. My data source for the occurrence of a march and the number of marchers comes from the Erica Chenoweth and Jeremy Pressman's Crowd Counting Consortium data, which records 656 distinct marches with between one and 725,000 total participants, including eight marches with over 100,000 participants. The Crowd Counting Consortium data is based on aggregating multiple sources, including media reports (which in turn primarily rely on police or government estimates of protest size), social media posts, and activist self-reporting.

In my primary tests I look at the number of marchers per capita in a county or congressional district. My population estimates (and thus my calculation of the per capita number of marchers) comes from the US census.

# **Dependent Variables**

I look at two specific avenues through which we can measure protest effectiveness: movement-building and political change. Within political change I look at both shifts in policymaking and in future electoral outcomes.

For movement-building, I look at the creation, size, and activity of groups associated with the "Indivisible" movement (Brooker 2018). Indivisible was started in December 2016 by a group of congressional staffers interested in spreading effective strategies of political engagement for people opposed to the "Trump agenda." Their "Indivisible: A Practical Guide for Resisting the Trump Agenda" encouraged concerned citizens to create local groups that would pressure elected officials to resist the Trump agenda (Bethea 2016). Indivisible groups often became the most prominent part of the activist space directly devoted to anti-Trump resistance.

I selected Indivisible groups as my measure of Resistance activity for several reasons. First, I was interested in the origins of new social movement activity, rather than mobilization through existing social movement organizations. Second, Indivisible is one of the few national networks of grassroots

organizations focused on the "Resistance agenda." Third, summary data on the geographic dispersion and size of groups was easily available for analysis.

My data on Indivisible groups comes from the listing of Indivisible groups on the main Indivisible website.<sup>3</sup> For rough estimates of the size of groups I investigated the public social media accounts associated with each group (typically a Facebook page) and recorded the number of members, as well as the levels of activity (frequency of posts and date of the most recent post). While the number of members in a Facebook group is certainly not a direct reflection of the absolute number of members active in a group, it is a reasonable rough proxy for the number of people in a local area who have expressed some interest in the Resistance and a ceiling on the number of likely active participants in Resistance activism in a local area.

For groups where no public social media data was available, a research assistant contacted the group at the email address publicly listed on the Indivisible website and requested information on the group's founding date, number of members, and the date of their most recent meeting. If Hypothesis 1 is correct, I expect that counties with Women's Marches should be much more likely to have Indivisible groups, and that these groups will in turn have larger numbers of members reported on social media and be more active.

For electoral outcomes, I look at the county or congressional-district vote share for the Democratic party in the 2018 elections to the House of Representatives. My data come from Dave Leip's election atlas of the United States. If Hypothesis 2 is correct, I expect that the number of Democratic votes in the 2018 election should be significantly higher in counties and congressional districts that experienced larger Women's Marches.

For policy shifts, I look at the DW-NOMINATE scores of congressional representatives in the 115th Congress (From January 2017 - January 2019), controlling for their score in the 114th congresss. DW-NOMINATE assigns scores along two ideological dimensions for each legislator based on roll-call voting. I select their scores along DW-NOMINATE's first dimension, which is roughly equivalent to a "left-right" or "liberal-conservative" spectrum (Poole 2005). The DW-NOMINATE scores come from the Voteview project at the University of California: Los Angeles (Lewis et al. 2019). If Hypothesis

<sup>&</sup>lt;sup>3</sup>www.indivisible.org

3 is correct, I expect that house members in districts with large Women's Marches should shift their DW-NOMINATE scores leftwards in response to the pressure

# **Control Variables**

I control for several plausible alternative explanations for both leftward political shifts in policymaking and election results and Resistance movement-building. First, I control for the democratic vote share in elections to the House of Representatives in 2014. I control for three demographic characteristics: the percentage of the population that identifies as white, black, and hispanic, based on census data. I also control for several economic indicators: median income, the unemployment rate, and the poverty rate.

# **Instrumental Variable Analysis**

As described above, one of the key drawbacks in much of the existing work on the effectiveness of protest is that, insofar as studies examining the impact of discrete protest events have been done, they are not able to fully account for the fact that the occurrence and size of protest is endogenous to existing political conditions. Thus any findings on the effectiveness of protest are subject to potential spuriousness. Studies have typically attempted to address this through the use of control variables to close off other observable explanations. However, this does not address potential unobservable factors influencing both protest size and political outcomes.

To address this objection, in my analysis of the Women's March I use a two-stage least-squares model with instrumental variables. Instrumental variables are the typical econometric technique for addressing the problem of endogenous independent variables. An instrumental variable affects an endogenous independent variable, but is itself exogenously assigned and only affects the dependent variable through its effect on the independent variable. While instrumental variables are common in economics, they are less frequently employed in social movement studies.<sup>4</sup>

I use average rainfall on January 21, 2017 as my instrument for the size of Women's March protests. <sup>4</sup>A search on Google Scholar of the terms "protest" and "instrumental variable" returned only seven articles from the American Sociological Review, five articles from Social Forces, and a single article from Mobilization.

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The use of rainfall as an exogenous predictor of public dissent, from protests and riots to organized violence, is well-established (Madestam et al. 2013; Ritter and Conrad 2016; Wasow 2017). Heavy rain and other forms of bad weather increase the personal discomfort and cost of engaging in protest. On rainy days fewer people are likely to turn out for a protest. For example, Hong Kong's pro-democracy "Umbrella Revolution" sit-in was significantly demobilized when its titular accessories failed to protect activists from sustained torrential downpours (Wan 2014). More recently, turnout for the 2019 third annual Women's March was significantly depressed by wintry weather associated with Winter Storm Harper (Ortiz 2019).

Rainfall on the day of the original Women's March is an ideal instrument for capturing the exogenous impact of protest size as well because it intuitively satisfies the "exclusion restriction," that is to say it has no plausible alternative connection to the longer-term outcomes I am measuring. While rainfall on election day may significantly effect voter turnout and swing elections (Gomez et al. 2007; Shachar and Nalebuff 1999), rainfall nearly two years before an election does not. Nor does a single day of rain plausibly affect the formation of activist groups and congressional voting patterns, except insofar as it affects critical events on that day: the Women's March itself.

My rainfall data comes from the National Oceanic and Atmospheric Administration (NOAA). NOAA collects data on several weather-related indicators from its more than 12,000 weather stations across the United States. I use NOAA's data on weather stations' location to create a grid of weather-station area polygons based on Voronoi tessellation (Voronoi 1908). The Voronoi tessellation algorithm draws the polygons around each weather station such that no point within a weather station's polygon is closer to any other weather station. To generate the weighted average rainfall across a county or congressional district I sum up the rainfall reported from each weather station whose Voronoi polygon intersects the county or congressional district in question, and then average them, weighting the average based on the percentage of the county or congressional district's area accounted for by each Voronoi polygon.<sup>5</sup>

This provides a more accurate weather estimate than simply giving equal weight to the average rainfall estimates from all weather stations inside a county or congressional district, as Madestam et al.

<sup>&</sup>lt;sup>5</sup>Thanks to Martin Smidt for suggesting the use of the Voronoi tessellation algorithm to calculate the geographic coverage of weather stations.

(2013) do, and addresses the problem that some small urban counties often do not have any weather stations inside their boundaries.

| Statistic             | N     | Mean        | St. Dev.    | Min   | Max        |
|-----------------------|-------|-------------|-------------|-------|------------|
| Marchers              | 3,141 | 1,089.306   | 13,940.330  | 0     | 451,223    |
| Marchers (per capita) | 3,141 | 0.002       | 0.014       | 0     | 0          |
| Rainfall (in)         | 3,134 | 0.148       | 0.339       | 0.000 | 3.425      |
| Dem. Vote Share 2018  | 3,110 | 0.361       | 0.178       | 0.000 | 1.000      |
| Dem. Vote Share 2014  | 3,105 | 0.330       | 0.187       | 0.000 | 1.000      |
| Percent White         | 3,141 | 0.847       | 0.164       | 0.039 | 0.993      |
| Percent Black         | 3,141 | 0.101       | 0.146       | 0.001 | 0.864      |
| Percent Hispanic      | 3,141 | 0.094       | 0.137       | 0.005 | 0.963      |
| Total Population      | 3,141 | 103,111.600 | 331,986.400 | 88    | 10,157,032 |
| Unemployment Rate     | 3,140 | 4.619       | 1.676       | 1.600 | 20.100     |

# FINDINGS

At this stage, data collection is only fully complete for the election models. Thus, I am only able to present preliminary results on the effects of the Women's March on the 2018 Democratic vote share.

Table 2 contains four models presenting these early results. Model 1 is a "naive" model showing the direct effect of participants in the 2017 Women's March per capita on the 2018 Democratic vote share, with no attend to take into account the endogenous elements of Women's March size. There is a positive and significant impact, however, this result is questionable because of the likely endogeneity problem.

Model 2 shows the first stage model in my instrumental variable analysis, testing whether rainy

|                         | Dependent variable:             |                    |  |                                  |  |  |
|-------------------------|---------------------------------|--------------------|--|----------------------------------|--|--|
|                         | Dem Share 2018                  | Marchers (pc)      | Dem Share 2018<br>instrumental<br>variable |                                  |  |  |
|                         | OLS                             | OLS                |  |                                  |  |  |
|                         | (1)                             | (2)                | (3)  | (4)                              |  |  |
| Marchers (pc)           | 0.972 <sup>***</sup><br>(0.121) |                    | 12.281*<br>(4.866)                         | 18.925** <sup>:</sup><br>(5.117) |  |  |
| Rainfall                |                                 | 0.002**<br>(0.001) |  |                                  |  |  |
| Rural/Urban             | 0.055***                        | 0.001*             | 0.042***                                   | 0.039***                         |  |  |
|                         | (0.003)                         | (0.001)            | (0.009)                                    | (0.006)                          |  |  |
| Dem. Vote Share 2014    | 0.703***                        | 0.017***           | 0.518***                                   | 0.610***                         |  |  |
|                         | (0.010)                         | (0.001)            | (0.082)                                    | (0.029)                          |  |  |
| Percent White           | -0.229***                       | -0.008*            | -0.137*                                    | -0.159**                         |  |  |
|                         | (0.022)                         | (0.003)            | (0.059)                                    | (0.035)                          |  |  |
| Percent Hispanic        | 0.077***                        | 0.002              | 0.056*                                     | 0.062***                         |  |  |
|                         | (0.012)                         | (0.002)            | (0.025)                                    | (0.016)                          |  |  |
| Percent Black           | -0.097***                       | -0.014***          | 0.051                                      | 0.015                            |  |  |
|                         | (0.023)                         | (0.003)            | (0.078)                                    | (0.045)                          |  |  |
| Unemployment Rate       | -0.00002                        | -0.001***          | 0.009*                                     | 0.004*                           |  |  |
|                         | (0.001)                         | (0.0002)           | (0.005)                                    | (0.002)                          |  |  |
| Constant                | 0.304***                        | 0.008*             | 0.210***                                   | 0.231***                         |  |  |
|                         | (0.023)                         | (0.003)            | (0.060)                                    | (0.037)                          |  |  |
| Observations            | 3,105                           | 3,103              | 3,103                                      | 3,071                            |  |  |
| $R^2$                   | 0.738                           | 0.061              | 0.005                                      | 0.555                            |  |  |
| Adjusted R <sup>2</sup> | 0.737                           | 0.059              | 0.002                                      | 0.554                            |  |  |

weather is a significant predictor of marchers per capita. Rainfall is indeed a significant predictor, though the sign on the coefficient is not in the expected direction.

Models 3 and 4 present initial results of the instrumental variable analysis. Model 3 replicates the naive model reported in Model 1, simply replacing Marchers per capita with marchers per capita instrumented by rainfall. The coefficient is positive and significant at the p < 0.05 level.

Model 4 refines Model 3 by removing outliers from the sample. Ninety-nine percent of counties have marchers per capita of less than five percent. However, a small number of counties have numbers much higher than this. The county with the highest number of marchers per capita is Washington County, Vermont, where the more than 17,000 reported participants in the Montpelier Women's March accounted for nearly 30% of the population. Since these outliers are so extreme relative to the total population, it is plausible that they might be driving any results. Thus in Model 4 I remove the 16 observations more than six standard deviations above the mean marchers per capita, which is roughly equivalent to any observation with a number of marchers per capita above 0.09.

The result increases both the size and level of significance for the instrumented measure of marchers per capita, suggesting that the extreme outliers were obscuring the effectiveness of the Women's Marches rather than driving it.

# CONCLUSION

This paper has used the 2017 Women's March as an example of a single "shock" event that allows for significant geographic disaggregation. In addition, it addresses the endogeneity of protest to current political conditions through an instrumental variable analysis using rainfall as an exogenous predictor of protest participation.

The early analysis provides some support for the argument that political protest can be broadly effective in leading to political change, and that a key factor in that effectiveness is protest size. The number of marchers per capita, instrumented by rainy weather, has a strong positive and significant relationship with the Democratic vote share in 2018, controlling for relevant political and demographic predictors (most importantly the previous mid-term election results).

Only the first stage of analysis for this project is currently completed. The next steps are to measure

the policy impact of the Women's Marches by looking at their effects on policymakers voting records. I am currently planning to incorporate the liberal-conservative dimension of the DW-NOMINATE scores for this purpose, but am also looking into voting scorecards from Planned Parenthood and other Women's Rights and reproductive rights organizations.

In addition, at this stage I am missing the crucial intervening aspect of movement-building through which I have argued the Women's Marches were likely to have their effect. Data collection on the Indivisible movement is ongoing, allowing tests of whether the Women's March significantly increased "Resistance" mobilization in the intervening period between the 2017 marches and the 2018 election.

The rainfall instrument has several positive qualities, but also some drawbacks. In particular, the date in question had remarkably good weather across much of the country. Thus the number of "rainy" counties is somewhat small. Future analysis could incorporate other measures of weather likely to influence protest turnout, for example deviations from typical temperature.

While the analysis is still only in its very early stages, it provides suggestive evidence for the power of political protest to affect change. Political protest, in particular large protests of the type seen in the 2017 Women's Marches, can have significant political impacts.

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