On-line Appendix: Explaining the Dynamics between the Women's Movement and the Conservative Movement in the U.S.

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A Research Design: Data and Measures

Table 1: Descriptive Statistics: 1960q1 to 1995q1*

	Mean	Standard Deviation	Minimum	Max
Pro-Feminist Events	5.12	4.57	0	26
Anti-Feminist Events	2.86	4.32	0	27
Democratic President	0.40	0.49	0	1
Democratic State Legislature	27.61	4.37	18	37
Δ Women's Movement Opinion	0.058	0.72	-1.80	2.69
Δ Women's Workforce	0.16	0.24	-0.5	1.10
Δ Women in Congress	0.27	2.14	-6	22
Δ Bill Passage*	0.01	1.05	-1	4

*Data Range 1960q1 to 1991q1

A.1 Dependent Variable

We model two sets of dependent variables: all women's movement events and all events that oppose the women's movement, as well as abortion rights and anti-abortion movement events. The event data are taken from the Dynamics of Collective Action data set, which assembled all collective action events from 1960 to 1995 reported in the daily editions of the *New York Times*. For a extensive description of the data collection process, see Walker, Martin, and McCarthy (2008, pp. 45-48) and Earl, Soule and McCarthy (2003). We aggregate by quarter the 1331 events which made claims related to the women's movements or abortion. These events were then coded according to whether they supported or opposed feminist positions. We define feminist events as those events which take positions combating any subordination on the basis of gender or seeking to improve the status of women. This includes events focused on combating sex discrimination; critiquing sex role stereotyping in all areas; supporting the Equal Rights Amendment and the expansion and protection of reproductive rights; advocating government support for mothers, poor women, and displaced homeowners; concerning the working conditions, pay, and benefits of all women workers; ad-

vocating increased funding for research specific to women; supporting gay and lesbian rights; advocating for family law reform; opposing violence against women; encouraging increased political representation of women and women's issues; advocating for the decriminalization of prostitution, and opposing pornography. The movement that arose in opposition to the feminist movement focused primarily on campaigns to oppose public policies that further the equality of the sexes, especially the passage of the Equal Rights Amendment, and the expansion of reproductive rights, including the legalization of abortion following the Supreme Court case *Roe V. Wade*. It is also opposed gay and lesbian rights, liberalized sex education, public funding for child care facilities, feminist curricula, and affirmative action. In addition, some movement events criticized specific claims of sex discrimination, domestic violence, and sexual harassment.

Because the valence coding in the Dynamics of Collective Action data can sometimes be misleading (Olzak 2010), all events that related to women or abortion were coded by hand by three coders (the two authors and one graduate assistant) using the what, where, why, and how fields as well as the title of the article. The specific coding of particular events and the code to retrieve the events that made claims about the women's movement are available by request from the authors. Cohen's kappa statistic is generally considered a robust measure of intercoder reliability across multiple coders (Lombard, Snyder-Duch & Bracken 2010, Landis & Koch 1977, Fleiss & Cohen 1973) since it takes into account the probability that coders could attach similar values by chance. In our case, Cohen's kappa indicated that there was high levels of intercoder reliability for both pro-feminist events (k=0.81, p=0.000) and anti-feminist events (k=0.87, p=0.000).

We recognize that this data set does not represent an unbiased or complete collection of all movement events. The extensive literature on the bias of event data gathered from newspapers suggests that our list of events is likely to represent large, dramatic events involving physical violence, formal organizations, or elites involved in policy making (McCarthy,

McPhail & Smith 1996, Oliver & Myers 1999, Oliver & Maney 2000). However, since our theories about how movements and the movements that oppose them react to one another focus on events with a high level of visibility, our measure is appropriate. Moreover, even though selection bias leads to only "newsworthy" events being reported, most researchers conclude that newspaper events remain a useful source of data and numerous studies in the area of social movements and conflict studies utilize such data (see Earl et al. 2004, King 2003, McCarthy, McPhail & Smith 1996, among others). In addition to "newsworthiness", the norm of presenting a balanced story may also influence the reporting of social movement events. In particular this leads to stories reporting greater conflict, potentially giving rise to oppositional movements (Meyer & Staggenborg 1996, Meyer & Staggenborg 2008, Gamson 1996). While this norm may influence the access of oppositional movements to the media, we do not expect this to advantage one of the oppositional movements over another or vary over time (Meyer & Staggenborg 2008). Second, our understanding of the balance norm exists within articles, thus if applying the norm of balance to articles about the feminist movement a reporter should be more likely to mention anti-feminist activity within the same article. Our decision to not classify counter-demonstrations reported in the same article as independent events (see discussion below) should mitigate any potential bias introduced. Several examples of the events that were coded are included in the main body of the article. Given that an event must be recorded to be analyzed and not all events are reported, we cannot know whether a comprehensive measure of all movement events would produce the same results. Our results do suggest, though, that within the public sphere, a movement's and its oppositional movement's activity affect each other. Future research should consider how the media, which serves as the mediator of the events in our data, influences the dynamic relationship between movements and their oppositional movements.

The Dynamics of Collective Action data set includes a code for counter-demonstrations staged at the same time as the event. We choose to only code the original event. This

Table 2: Robustness Check Events Plus Counter Events

	Movement	Opposition Movement
	β (SE)	β (SE)
Anti-Feminist Events$_t$	0.06**	–
	(0.02)	
Feminist Events$_t$	–	0.15**
		(0.03)
Democratic President$_t$	-0.02	0.29
	(0.04)	(0.25)
Democratic State Legislatures$_t$	0.02†	-0.07*
	(0.01)	(0.03)
Δ Women's Movement Opinion$_{t-2}$	-0.13†	0.37**
	(0.07)	(0.15)
Δ Women's Movement Opinion$_{t-3}$	-0.05	–
	(0.05)	
Δ Women's Workforce$_{t-3}$	0.08	–
	(0.07)	
Δ Women's Workforce$_{t-4}$	–	-0.36
		(0.36)
Δ Women in Congress$_{t-1}$	-0.03†	0.08**
	(0.02)	(0.02)
Intercept	1.36**	1.65**
	(0.39)	(0.57)
ρ_1	0.09	0.27**
	(0.07)	(0.07)
ρ_2	0.16*	0.15**
	(0.07)	(0.06)
ρ_3	0.21**	0.08
	(0.07)	(0.07)
Wald Statistic	14.94	32.42
pr > Wald	0.002	0.0001
Log-Likelihood	-319.32	-251.74
AIC	658.65	521.48
Degrees of Freedom	129	129

Temporal Domain:1960-1995
Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$
Standard errors in parentheses.

decision provides us with a more conservative estimate of the interactions between these opposing movements. To check the influence this decision might have had on our findings we re-created our feminist and anti-feminist event series, adding these counter-demonstrations,

and then ran our models using these alternatives measure. Results for this robustness check are reported in Table 2. The results reported in the manuscript are robust to this alternative specification of our event measures.

A.2 Control Variables

We use the number of pieces of feminist legislation which were passed by the House and the Senate and became law as a measure of movement success. To calculate this measure we used Christina Wolbrecht's (2000) data on bill sponsorship and co-sponsorship of feminist legislation to create a list of feminist bills proposed in each session of Congress. We then researched the legislative history of each bill to determine when and if the bills became law, and added up the number of pieces of legislation that became law in each quarter. These data are only available until 1992, so inclusion of this variable reduces the length of our time series.

We use two measures of political opportunities: party control of state legislatures and party of the president. Party control of the state legislature is the number of state legislatures under the control of the Democratic Party. Party control of the presidency is measured by a dummy variable series with 1 indicating that a Democrat is in the White House. However, presidential support or opposition to the women's movement may be specific to presidential administrations; Banaszak (2010) notes that many Republican presidents in the early years of the women's movement were more supportive than Republican presidents in later years. We tested an alternative specification by creating dummy variables for each presidential administration, excluding one presidential term in our analysis. We find that there is variation across presidential administrations in the number of events. The results for the key variables reported in the manuscript above are robust to this alternative specification.

We include three measures designed to capture both political and social opportunities in our analysis: women's workforce participation, the number of women in the U.S. Congress,

and public opinion about gender. We note that McCammon et al. (2001) argue changes in women's roles may in part reflect movement success given that one goal is change in women's roles. However, because other economic, political, and social factors also influence the status of women we do not assume these variables represent movement outcomes here.

First, we control for women's increased workforce participation by the proportion of women 16 years or older in the civilian labor force.[1] The second measure of social, political, and economic changes related to women is a count of the number of women serving the U.S. Congress provided by Center for American Women and Politics (CAWP 2010). This measure helps us capture the political opportunities available to women.

Our third measure of social, political, and economic changes related to women –public opinion on gender– requires more extensive explanation. We sought a public opinion measure specific to the particular type of events captured in the dependent variable. Most measures of gender attitudes create problems for time series research because the questions are not asked consistently, at regular intervals, and at a frequency that corresponds with other political phenomena we are interested in analyzing. To overcome these problems we construct a single measure of public opinion about gender attitudes over time using an algorithm developed by James Stimson to create public policy mood (Stimson 1991, Ondercin 2007, Banaszak & Ondercin Forthcoming). For technical details about how to calculate the measure please see Stimson (1991). The logic underlying the measure is that all the questions about gender are tapping a latent trait. The algorithm then uses the shared variation in public opinion questions to estimate the latent concept, in our case attitudes about gender.

The gender attitudes series is based on 205 survey questions about the roles of men and women in society and different gender related policies. Each survey question was asked at least twice using the exact same question wording. Survey questions that are very similar but have small question wording changes are counted as different questions to ensure that no movement in the series artificially results from a change in wording. Questions were gathered

from iPoll the Roper Center's on-line archive of public opinion data and National Election Studies. Eight Roper-defined categories were used to identify questions on iPoll: women, men, equality, work, family, rights, abortion and sex. The measure is coded such that higher scores reflect more liberal attitudes defined as responses that indicate equality between men and women or minimize the differences between the sexes. Questions were excluded if the response categories did not provide a clear indication of liberal or conservative position.

As a result of how the measure is calculated the resulting series has an artificial metric, which means that there is no inherent meaning to say the 50 point mark like there is with a traditional measure of public opinion. We cannot say that 50% of the population agrees with some position or holds a certain set of attitudes. However, change in the levels of the series are still meaningful. If we move, say from 50% to 60% we can say there is a 10% increase in support for gender attitudes.

When modeling all women's movement and anti-feminist movement events we use a general measure of gender attitudes. When modeling the abortion rights and anti-abortion movements we use measures of public opinion on abortion constructed using the same method as the gender attitudes measure. All public opinion measures are specified as the first difference in the models.

A.3 Time Series and Frequency

We use time series methods to analyze the quarterly series of pro-feminist and anti-feminist events. Given our interest in the dynamics between national movements, time series methods offer the appropriate level of aggregation and provide the most direct test of our hypotheses. Selecting the appropriate frequency to construct our measures and carry out the analysis can be tricky. With longer time periods, such as yearly or bi-yearly data, the analysis could miss the dynamics we wish to study. Shorter time periods, such as daily or weekly data, are unfeasible because of a lack of variation in our dependent and some of

our control variables. Additionally, the finer units of time contain a considerable amount of missing data; 28% of all event days and 17% of all event months are missing. If we rely on the report date instead of the actual event date we would introduce a considerable amount of measurement error. Specifically, in 97% of cases the event occurred on a different date than the date on which the story reporting the event appeared in the *New York Times*. At the monthly level, 30% of the stories appear in a different month than when they reported. Higher levels of aggregation reduce this measurement error. Thus, the quarterly level of aggregation provides a fine enough unit of analysis to capture the dynamics we are interested in and long enough unit of analysis to reduce measurement error.

A quarterly analysis allows us to best capture the dynamic behavior we wish to explore. We expect that, in most cases, movements and the movements that oppose them respond reasonably quickly to each others' actions, and, as a result, we selected a frequency for our analysis that would best capture this process. We acknowledge that this frequency may miss responses that are occurring at a faster rate, thus we can view our results as a conservative estimate of the dynamic relationship between oppositional movements. Additionally, we believe that the quarterly analysis best allows us to capture the relationship between mobilization and our other independent variables. For example, when a movement is successful we expect the movement opposing it will mobilize quickly to try to reverse that success instead of waiting until the next legislative session (a two-year time period) to respond. Moreover, larger time periods are likely to impede our ability to examine short-term and long-term effects since some of those effects will appear to be simultaneous if the time periods are larger. A quarterly analysis therefore allows us to better identify the responses of opposing movements to each other and to their successes.

We also ran a set of analysis on monthly data to ensure that our results were not a function of the quarterly unit-of-analysis. When the event month was missing we substituted the report month, unless we had an indication that the event occurred in a month different

than the report month. If it was indicated that the event occurred in a month different than the report month, we assigned the event to the month before the report month. This robustness check can be found in Table 3. The results reported in the manuscript are robust to this alternative specification.

Table 3: Robustness Check On Event Frequency, Monthly 1963-1995

	Movement	Opposition Movement
	β (SE)	β (SE)
Anti-Feminist Events$_t$	0.11**	–
	(0.02)	
Feminist Events$_t$	–	0.20**
		(0.03)
Democratic President$_t$	-0.12	-0.30
	(0.09)	(0.25)
Democratic State Legislatures$_t$	0.08**	-0.02
	(0.01)	(0.02)
Δ Women's Movement Opinion$_{t-2}$	0.07	-0.13
	(0.15)	(0.24)
Δ Women's Movement Opinion$_{t-3}$	-0.01	–
	(0.16)	
Δ Women's Workforce$_{t-3}$	0.09	–
	(0.15)	
Δ Women's Workforce$_{t-4}$	–	0.91
		(0.65)
Δ Women in Congress$_{t-1}$	-0.06	0.14**
	(0.05)	(0.02)
Intercept	-1.26**	0.22
	(0.43)	(0.48)
ρ_1	0.23**	0.24**
	(0.06)	(0.06)
ρ_2	0.08	0.12*
	(0.06)	(0.06)
ρ_3	0.12†	0.09
	(0.06)	(0.06)
Wald Statistic	40.53	37.36
pr > Wald	≤ 0.001	≤ 0.001
Log-Likelihood	-718.62	-468.00
AIC	1457.231	954.00
Degrees of Freedom	417	382

Temporal Domain:1963-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

A.4 PAR(ρ): Model Specification

To model time series event count data we have two options: the Poisson Autoregressive model (PAR(ρ)), designed for mean reverting count data, and the Poisson Exponential Weighted Moving Average model (PEWMA), designed for highly persistent time series count data (Brandt et al. 2000, Brandt & Williams 2001). The autocorrelation function (ACF) and partial autocorrelation function (PACF) for each of the dependent variables are used to select between these two models (Brandt & Williams 2001). All the series show moderate correlations in the ACF that decay over time. The decay rates are not steady, suggesting a higher order AR process. The PACF also indicates a higher order AR process, with between 2 or 3 significant spikes, depending on the series. Based on the ACF and PACF we specified a variety of AR processes. The AIC (Akaike information criterion) statistic indicates AR(3) best fits the data. Diagnostic analyses suggest the Poisson Autoregressive model is the best option for our data. Additionally, we used the ACF and PACF to assess the possibility of seasonal trends in the series (Box-Steffensmeier et al. 2014). For example, we might expect more events in summer when the weather is more conducive to outside protests. There is not evidence that the ACF and PACF contain seasonal trends. One reason why this might be the case is that our event measure includes non-protest events, which would not be subject to the weather. Another reason the data may lack seasonal trends is that the events are geographically dispersed across the United States. Thus when it is cold and snowy in the Midwest and Northeast weather is prime for organizing in the South and West and summer may reduce outdoor protests in the south.

Estimation of the PAR(ρ) is relatively straightforward and was conducted in R. Code for estimating the PAR(ρ) can be found at `http://www.utdallas.edu/~pbrandt/pbrandt/Code_%26_Software.htm|`. Both the order of the autoregressive process and the lag lengths of the variables were determined by which model produced a significantly lower AIC information criteria. While we have theoretical expectations that there is a dynamic relationship

underlying the activities of the women's movement and anti-feminist movement, as well as our covariates, our theoretical argument does not precisely identify the dynamic nature of these relationship. Instead, we depend on a variety of statistical tests to assess the best model specification in terms of the autoregressive process and the lag lengths for the covariates.

B Summary of Additional Robustness Checks

We ran a series of robustness checks to examine the effect of model specification. Below is a brief summary of these robustness checks and the results. For full results of the robustness checks please contact the authors. We find similar dynamic relationships across these different robustness checks.

B.1 Movement Resources:

Some social movement literature focuses on the amount of resources different organizations have to carry out their agenda (Minkoff 1995, McCarthy & Zald 1977, Rohrschneider & Dalton 2002). However, our analyses do not include a measure of resources. While it is reasonable to expect resources to influence an organization's ability to carry out an event, our analyses focus on the macro behavior of national movements and not specific organizations. Weldon (2002) notes that characteristics of an individual social movement organization may not resemble the characteristics of the movement as a whole. As a result, the influence of resources may be obscured by the level of aggregation. If one organization expends all of its resources to engage in a public action event, we expect that other organizations within the movement still retain the capacity to respond to counter-events. Moreover, because our analysis is of movements and not specific actors within the movements, reliable measures for the resources of the entire movement do not exist and would be extremely difficult to create. To try to capture movement resources we use the count of women's organizations

from Minkoff (1995). There are some limitations to this data. First, since members, financial resources, or other forms of institutional support are the primary resources identified in the literature (see for example Minkoff (1995, p.78)), the number of organizations only gives us a general sense of the resources potentially available to the women's movement. Second, these data are only available on a yearly basis between 1955-1985. Tables 4 and 5 include the models presented in the manuscript and also models that control for changes in organizational resources. Despite more limited time frame for this, data reducing the number of cases by approximately 30%, the central relationship between movements and opposition movements reported below continue to hold.

Table 4: Comparison Womens Movement Model Including Women's Organization, Quarterly 1960-1985

	Model 1	Model 2	Model 3	Model 4
Anti-Feminist Events$_t$	0.21**	0.22**	0.20**	0.21**
	(0.06)	(0.06)	(0.06)	(0.06)
Democratic President$_t$	0.01	-0.05	-0.26	-0.26
	(0.52)	(0.43)	(0.37)	(0.38)
Democratic State Legislatures$_t$	0.02	0.01	0.05	0.04
	(0.06)	(0.05)	(0.05)	(0.05)
Δ Women's Movement Opinion$_{t-2}$	-1.01**	-0.94**	-0.94**	-0.96**
	(0.38)	(0.37)	(0.36)	(0.36)
Δ Women's Movement Opinion$_{t-3}$	-0.30	-0.27	-0.41†	-0.39†
	(0.23)	(0.23)	(0.24)	(0.24)
Δ Women's Workforce$_{t-3}$	1.07	0.98	0.41	0.42
	(1.09)	(0.95)	(0.81)	(0.85)
Δ Women in Congress$_{t-1}$	0.47†	0.45†	0.34	0.37†
	(0.26)	(0.24)	(0.22)	(0.22)
Δ Bill Passage	–	–	-5.27	-4.50
			(9.68)	(7.10)
Δ Women's Organizations	–	0.01	–	0.01
		(0.03)		(0.02)
Intercept	0.23	0.38	-0.13	0.06
	(2.02)	(1.65)	(1.48)	(1.38)
ρ_1	0.15	0.15	0.12	0.13
	(0.10)	(0.10)	(0.09)	(0.09)
ρ_2	0.33**	0.37**	0.35**	0.38**
	(0.09)	(0.10)	(0.09)	(0.10)
ρ_3	0.35**	0.31**	0.37**	0.34**
	(0.10)	(0.10)	(0.10)	(0.10)
Wald Statistic	113.43	100.31	222.39	222.06
pr > Wald	< 0.001	< 0.001	< 0.001	< 0.001
Log-Likelihood	-191.97	-189.49	-188.74	-186.68
AIC	403.95	400.99	399.48	397.37
Degrees of Freedom	92	90	91	89

Temporal Domain: 1960-1985

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

Table 5: Comparison Anti-Womens Movement Model Including Women's Organization, Quarterly 1960-1985

	Model 5	Model 6	Model 7	Model 8
Feminist Events$_t$	0.13**	0.10**	0.13**	0.14**
	(0.05)	(0.03)	(0.04)	(0.04)
Democratic President$_t$	-0.20	0.01	-0.03	-0.03
	(0.37)	(0.21)	(0.26)	(0.26)
Democratic State Legislatures$_t$	-0.03	-0.01	-0.01	-0.003
	(0.03)	(0.03)	(0.03)	(0.03)
Women's Movement Opinion$_{t-2}$	0.10	0.17	0.23	0.19
	(0.23)	(0.17)	(0.23)	(0.23)
Δ Women's Workforce$_{t-4}$	-0.73	-0.27	-0.17	-0.13
	(0.91)	(0.43)	(0.42)	(0.46)
Δ Women in Congress$_{t-1}$	0.16	0.09	0.05	0.03
	(0.12)	(0.09)	(0.10)	(0.09)
Δ Bill Passage	–	–	-1.47	-1.95
			(1.03)	(1.95)
Δ Women's Organizations	–	-0.13*	–	-0.13*
		(0.06)		(0.06)
Intercept	1.00	0.72	0.57	0.41
	(0.78)	(0.58)	(0.66)	(0.71)
ρ_1	0.37**	0.28**	0.36**	0.32**
	(0.12)	(0.12)	(0.11)	(0.11)
ρ_2	0.05	-0.08	0.13	0.11
	(0.14)	(0.14)	(0.11)	(0.11)
ρ_3	0.08	0.16	0.03	0.08
	(0.12)	(0.11)	(0.10)	(0.09)
Wald Statistic	11.55	9.65	19.18	19.16
pr > Wald	0.01	0.05	<0.001	<0.001
Log-Likelihood	-132.71	-126.63	-127.16	-121.16
AIC	283.41	273.26	274.31	264.32
Degrees of Freedom	93	91	92	90

Temporal Domain: 1960-1985

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

B.2 Bill Introductions:

A Movement and its oppositional movement may also be responding to external factors, such as the proposal of feminist or anti-feminist legislation. We examined this possibility by using a count of pro-feminist and anti-feminist bills that were introduced to Congress, reported in Table 6. First, both the pro-feminist bill introduction and the anti-feminist bill introduction measures are insignificant. Second, while there are some changes in magnitude of the coefficients, the results reported in the paper remain robust to various specifications. We recognize that bill introductions do not capture the entire legislative process, but they do provide us one indicator of activity.

Table 6: Robustness Checks Bill Introductions

	Movement	Opposition Movement
	β (SE)	β (SE)
Anti-Feminist Events$_t$	0.14**	–
	(0.04)	
Feminist Events$_t$	–	0.08**
		(0.03)
Democratic President$_t$	-0.12	-0.02
	(0.45)	(0.17)
Democratic State Legislatures$_t$	0.01	-0.02
	(0.07)	(0.02)
Δ Women's Movement Opinion$_{t-2}$	-1.01*	0.22*
	(0.47)	(0.11)
Δ Women's Movement Opinion$_{t-3}$	-0.48	–
	(0.39)	
Δ Women's Workforce$_{t-3}$	0.61	–
	(0.90)	
Δ Women's Workforce$_{t-4}$	–	-0.13
		(0.26)
Δ Women in Congress$_{t-1}$	0.23	0.03
	(0.18)	(0.06)
Δ Feminist Bill Introductions	0.0001	-0.00001
	(0.01)	(0.002)
Δ Anti-feminist Bill Introductions	0.03	0.03
	(0.06)	(0.04)
Intercept	0.81	1.02**
	(2.05)	(0.03)
ρ_1	0.13†	0.17*
	(0.07)	(0.08)
ρ_2	0.35**	0.08
	(0.08)	(0.08)
ρ_3	0.36**	0.05
	(0.08)	(0.08)
Wald Statistic	142.74	8.59
pr > Wald	0.001	0.04
Log-Likelihood	-259.474	-204.0443
AIC	542.94	430.0887
Degrees of Freedom	114	115

Temporal Domain: 1960-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

B.3 Heterogeneity in Size and Violence of Events:

We might expect variation across different types of events. Previous research (McAdam & Su 2002, Walker, Martin & McCarthy 2008) shows that police violence reduces mobilization and very large (and therefore publicly visible) protest events increase the opposing movement's mobilization. As a robustness check, we assessed these possibilities although both it is rare when looking at women's movement/countermovement events to find either police violence or very large events. Table 7 reports the results with measure of event heterogeneity and events with violence. The results reported in this paper remain robust to the inclusion of a measure of the number of events each quarter with 10,000 or more participants and two measures of police action – the number of events where the police used physical tactics in that quarter and the events where the police used violence against protesters in that quarter. We omit these controls from our analysis to keep the models as parsimonious as possible given our limited number of time points, and because the measures have some limitations which make them less accurate than we would like. For example, the measures of violence are event counts of police violence but they do not indicate who was the target of the attack – only whether violence was used.

Table 7: Robustness Check Size and Violence of Events

	Movement	Opposition Movement
	β (SE)	β (SE)
Anti-Feminist Events$_t$	0.03*	–
	(0.01)	
Feminist Events$_t$	–	0.07**
		(0.02)
Democratic President$_t$	-0.06	0.08
	(0.07)	(0.10)
Democratic State Legislatures$_t$	0.03	-0.02
	(0.02)	(0.01)
Δ Women's Movement Opinion$_{t-2}$	-0.16	0.11
	(0.10)	(0.09)
Δ Women's Movement Opinion$_{t-3}$	-0.09	–
	(0.10)	
Δ Women's Workforce$_{t-3}$	0.10	–
	(0.10)	
Δ Women's Workforce$_{t-4}$	–	-0.16
		(0.18)
Δ Women in Congress$_{t-1}$	-0.04	0.06**
	(0.03)	(0.01)
Large Events	0.22**	0.09
	(0.08)	(0.10)
Police 3	0.14	0.19*
	(0.11)	(0.09)
Police 4	0.77**	0.50†
	(0.23)	(0.27)
Intercept	0.70	0.90*
	(0.71)	(0.36)
ρ_1	0.09	0.19**
	(0.07)	(0.06)
ρ_2	0.17*	0.09
	(0.08)	(0.05)
ρ_3	0.19*	0.04
	(0.10)	(0.06)
Wald Statistic	7.47	16.21
pr > Wald	0.06	0.001
Log-Likelihood	-283.83	-237.70
AIC	593.65	499.40
Degrees of Freedom	126	126

Temporal Domain:1960-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

B.4 Historical Time Periods:

Some authors break the second wave into different time periods marked by the occurrence of specific events (Ryan 1992, Meyer & Staggenborg 2008). The Equal Rights Amendment's passage in the U.S. Congress and the Supreme Court's decision in *Roe v. Wade* might be considered particularly important events that might alter the relationship between opposing movements. We ran a series of robustness checks that included variables to control for these specific events. Table 8 reports the results of step functions controlling for the passage of the ERA and court's decision in Roe, coded 1 in the quarter of the event (ERA passage or Roe decision) and then 1 for the remaining series. Due to issues with convergence in the models of the oppositional movement controls for the ERA and Roe were had to be tested in separate models. Our results remain consistent even when these events are explicitly modeled. Several of the relationships, in particular those associated with the anti-feminist movement, become stronger with these controls in the model.

Table 8: Robustness Checks For Historical Time Periods

	Movement	Opposition Movement	Opposition Movement
	β	β	β
	SE	SE	SE
Anti-Feminist Events$_t$	0.06**	—	—
	(0.02)		
Feminist Events$_t$	—	0.12**	0.12**
		(0.02)	(0.01)
Democratic President$_t$	-0.13	0.07	-0.0001
	(0.10)	(0.18)	(0.18)
Democratic State Legislatures$_t$	0.06**	-0.09**	-0.10**
	(0.02)	(0.02)	
Δ Women's Movement Opinion$_{t-2}$	-0.18†	0.15	0.17†
	(0.10)	(0.09)	(0.09)
Δ Women's Movement Opinion$_{t-3}$	-0.13	—	—
	(0.10)		
Δ Women's Workforce$_{t-3}$	0.12	—	—
	(0.18)		
Δ Women's Workforce$_{t-4}$		-0.65	-0.48
		0.38	(0.35)
Δ Women in Congress$_{t-1}$	-0.04	0.07**	0.06**
	(0.03)	(0.01)	(0.02)
ERA	1.02**	0.91**	
	(0.38)	(0.37)	
Roe	-0.78**		0.96**
	(0.36)		(0.34)
Intercept	-0.43	2.17**	2.37**
	(0.69)	(0.60)	(0.62)
ρ_1	0.02	0.19**	0.19**
	(0.07)	(0.06)	(0.06)
ρ_2	0.18**	0.09	0.09
	(0.08)	(0.06)	(0.05)
ρ_3	0.28**	-0.01	-0.01
	(0.08)	(0.07)	(0.07)
Wald Statistic	18.88	15.72	14.16
pr > Wald	<0.001	0.001	0.003
Log-Likelihood	-290.73	-239.85	-238.68
AIC	605.46	499.69	497.36
Degrees of Freedom	127	128	128

Temporal Domain: 1960-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

B.5 Organizational Presence:

There might also be different dynamics when movement organizations are present at an event compared to events without an movement organization. First, for the feminist movement we created a quarterly series of events where a social movement organization was identified as being present and a series of events where no social movement organization was identified. Second, we created two quarterly series for the anti-feminist movement, one of events where a social movement organization was identified and one without a social movement organization identified. We have some concerns about measurement error associated with the organizational code in the DCA data. The DCA data does contain a variable indicating whether a social movement organization was mentioned as participating in the collect action event. We will only observe social movement organizations present when the reporter chooses to include the organization in the news story. There are likely organizations present at many of the collective action events but this information was omitted for the news report.

Of the pro-feminist events 54.37% had an organizational presence identified. Of the anti-feminist events 42.54% of the events had an organizational presence identified. We began by looking at how closely these event series resembled each other. The correlation between the two womens movement series was 0.52 and the two anti-feminist event series (with and without social movement organizations) correlated at 0.62.

Given the correlations between these series and our limited number of data points, we have concerns with multicollinearity reducing the precision of our estimates. We proceeded to estimate two models with feminist events as our dependent variable, substituting in and out our two measures of anti-feminist events. These results are presented in Table 9. The central findings of our manuscript remain robust when we examine only events with an organizational presence and only events without an organization presence. Also, the coefficients for the events series with social movement organizations and the coefficients for the events series without social movement organizations are remarkably similar. Given the high correlation

Table 9: Robustness Checks on Organizational Presence

	Movement		Opposition Movement	
	SMO Present	No SMO Present	SMO Present	No SMO Present
Anti-Feminist Events$_t$ with SMP Present$_t$	0.13**	–	–	–
	(0.03)			
Anti-Feminist Events$_t$ without SMP Present$_t$	–	0.11**	—	
		(0.04)		
Feminist Events$_t$ with SMP Present$_t$	–	–	0.06**	–
			(0.02)	
Feminist Events$_t$ without SMP Present$_t$	–	–	–	0.06**
				(0.01)
Democratic President$_t$	-0.09	-0.13	-0.01	-0.001
	(0.09)	(0.13)	(0.05)	(0.05)
Democratic State Legislatures$_t$	0.04	0.05†	-0.002	-0.003
	(0.02)	(0.03)	(0.001)	(0.01)
Women's Movement Opinion$_{t-2}$	-0.13	-0.018	0.09	0.08
	(0.10)	(0.13)	(0.06)	(0.06)
Women's Movement Opinion$_{t-3}$	-0.11	-0.15		
	(0.10)	(0.14)		
Δ Women's Workforce$_{t-3}$	0.11	0.11		
	(0.13)	(0.17)		
Δ Women's Workforce$_{t-}$	–	–	0.004	-0.03
			(0.08)	(0.07)
Δ Women in Congress$_{t-1}$	-0.4†	-0.05†	0.04*	0.02†
	(0.03)	(0.04)	(0.02)	(-0.01)
Intercept	0.53	0.12	1.10**	1.28**
	(0.78)	(0.97)	(0.22)	(0.22)
ρ_1	0.04	0.04	0.11*	0.11*
	(0.07)	(0.06)	(0.05)	(0.05)
ρ_2	0.23**	0.21**	0.05	0.04
	(0.08)	(0.07)	(0.05)	(0.05)
ρ_3	0.29**	0.40**	0.09†	0.08
	(0.08)	(0.08)	(0.05)	(0.06)
Wald Statistic	30.43	49.34	8.84	6.82
pr $\leq$ Wald	$\leq$ 0.0001	$\leq$0.0001	0.03	0.08
Log-Likelihood	-296.31	-299.51	-248.62	-252.21
AIC	612.61	619.02	515.24	522.42
Degrees of Freedom	129	129	129	129

Temporal Domain: 1960-1995

Two-tailed Significance Tests: †: p $\leq$ 0.1; * : p $\leq$ 0.05; ** : p $\leq$ 0.01

Standard errors in parentheses.

between the events series with and without social movement organizations and the similar magnitude of their coefficients, we feel that it is best to combine the two types of events into a single measure.

B.6 Geographical Controls:

To address the possibility that our results are spurious because of a lack of geographical controls, we restricted the data set to events occurring only in one geographical region. Given the location of the New York Times and the geographical bias towards the New York region the use of this newspaper introduces into the data, the only region with enough events to carry out any statistical analysis was the Northeast. We define the Northeast as Connecticut, Washington D.C., Delaware, Massachusetts, Maryland, New Hampshire, New Jersey, Pennsylvania, Rhode Island, Virginia, and West Virginia (there were no events in Vermont). There were a total of 869 events occurring in the Northeast, which represents 65% of the total events we studied in the manuscript. Table 10 reports re-estimated models on event count data created from events geographically restricted to the Northeast. Because of this restriction, analysis starts in 1966. Our primary findings about the relationship between the women's movement and its oppositional movement are robust when we geographically restrict the data. Moreover, the magnitude of the coefficients increase, suggesting an even stronger relationship between movements and oppositional movements when we focus on more regional data. It appears that by not restricting the data geographically in the manuscript we biased our results downward due to the increased noise. Further, and more importantly, our results are not spuriously driven by geography.

Table 10: Robustness Checks Northeast Events Only, Quarterly 1966-1995

	Movement	Opposition Movement
	β (SE)	β (SE)
Anti-Feminist Events$_t$	0.15**	–
	(0.04)	
Feminist Events$_t$	–	0.14**
		(0.04)
Democratic President$_t$	-0.71*	-0.27
	(0.31)	(0.32)
Democratic State Legislatures$_t$	-0.04	-0.03
	(0.03)	(0.02)
Δ Women's Movement Opinion$_{t-2}$	-0.70**	0.22
	(0.27)	(0.15)
Δ Women's Movement Opinion$_{t-3}$	-0.11	–
	(0.16)	
Δ Women's Workforce$_{t-3}$	0.47	–
	(0.69)	
Δ Women's Workforce$_{t-4}$	–	-0.34
		(0.53)
Δ Women in Congress$_{t-1}$	-0.02	0.07†
	(0.08)	(0.04)
Intercept	2.27**	0.79
	(0.86)	(0.57)
ρ_1	0.16*	0.19*
	(0.08)	(0.09)
ρ_2	0.36**	0.06
	(0.08)	(0.09)
ρ_3	0.12	0.10
	(0.08)	(0.12)
Wald Statistic	48.73	7.38
pr > Wald	< 0.001	0.06
Log-Likelihood	-260.89	-185.63
AIC	541.79	389.25
Degrees of Freedom	118	119

Temporal Domain: 1966-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Standard errors in parentheses.

B.7 Endogenity:

In the Gaussian time series framework, the Granger Causality test is commonly employed to determine if there is an endogenous relationship between two variables (Freeman 1983, Granger & Newbold 1974). It is inappropriate to use this method on an event count time series because of the distributional mismatch. However, as a robustness check we transformed the events counts into the z-score of the event count series to obtain a continuous distribution and then ran Granger Causality tests. The null hypothesis for the Granger Causality tests is that one variable does not Granger cause the other variable. Failing to reject one of the null hypotheses indicates a lack of an endogenous relationship. In this case we fail to reject both the null that the feminist movement events do not Granger cause anti-feminist movement events and anti-feminist movement events do not Granger cause feminist events. Granger Causality has two limitations. First, it cannot test if two series are contemporaneously correlated. Second, it may not detect endogeneity between two variables if the two variables react to one another at a faster rate than we observe the data. Table 11 reports the results of the Granger Causality tests. The results for anti-feminist and feminist movement event supports the results reported in Table 1 in the manuscript.

Similar to the pro-feminist and anti-feminist movements, we converted the abortion rights and the anti-abortion rights event counts into z-scores to provide a continuous distribution in order to conduct Granger Causality tests. We fail to reject the null that abortion rights events do not Granger cause anti-abortion events. However, we can reject the null that anti-abortion events do not Granger cause abortion rights events. Because Granger causality is not found going in both directions we once again can conclude the possibility of endogeneity is limited.

Table 11: Granger Causality Tests, Quarterly 1960-1995

Relationship	F-test
Anti-feminist Events$_{t-1}$ Dose Not Granger Cause Feminist Events$_t$	0.15
Feminist Events$_{t-1}$ Dose Not Granger Cause Anti-feminist Events$_t$	0.02
Anti-abortion$_{t-1}$ Dose Not Granger Cause Abortion Events$_t$	6.14**
Abortion$_{t-1}$ Dose Not Granger Cause Anti-abortion Events$_t$	0.67

Temporal Domain: 1960-1995

Two-tailed Significance Tests: †: $p \leq 0.1$; $*$: $p \leq 0.05$; $**$: $p \leq 0.01$

Based on 4 lags

Notes

[1]Data downloaded from the Bureau of Labor Statistics: `http://www.bls.gov/data/#employment`. Series id: LNS11300002Q. Seasonally adjusted.

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