Supplementary material for *Female employment and voter turnout – Evidence from India*

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A Data and estimation sample

In this section, we provide details on the data construction and the estimation sample.

A.1 Polling booth data

We first provide details on the polling booth dataset by Susewind (2016).

Measuring turnout rates

We construct measures of turnout rates based on the following variables: total number of votes (*turnout*), number of male votes (*male_votes*), total number of eligible voters (*electors*) and share of eligible voters being females (*women_percent*). Since we do not have any microdata we are unable to conduct more disaggregated analyses of, for example, different types of women and men.

Some observations in the data are clearly misreported. In particular, the variable *women_percent* has too high values in 2017, while the variable *electors* has too low values for many observations in 2014. In our main measures, we therefore ignore these variables in the particular years. We construct our measure of female turnout in 2014 and 2017 as follows:

$$Turnout\ Females_{2014} = \frac{turnout_{2014} - male_votes_{2014}}{((electors_{2012} + electors_{2017})/2) * women_percent_{2014}}$$

$$Turnout\ Females_{2017} = \frac{turnout_{2017} - male_votes_{2017}}{electors_{2017} * women_percent_{2014}}$$

Male turnout is measured in a similar fashion. In addition to these measures, we construct the following alternative turnout rate for 2014, using the number of eligible voters in 2014 directly, instead of averaging over 2012 and 2017:

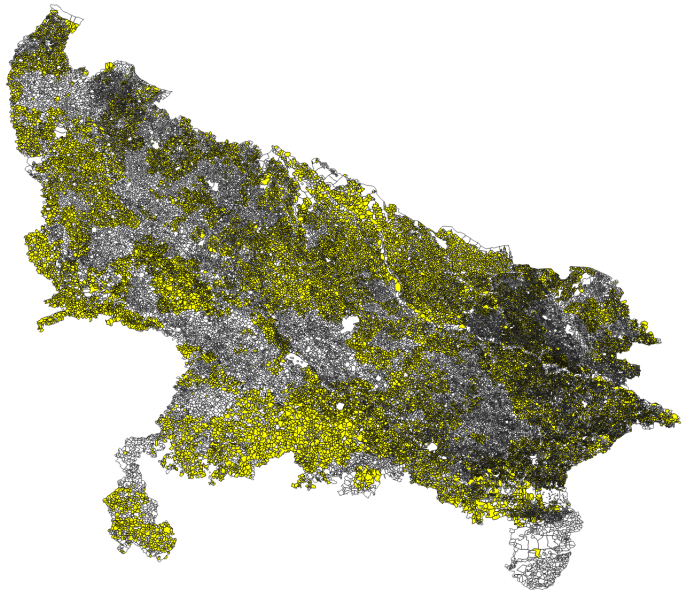
$$Turnout\ Females_{2014,alt} = \frac{turnout_{2014} - male_votes_{2014}}{electors_{2014} * women_percent_{2014}}$$

Constructing the sample

The Susewind (2016) dataset covers close to all polling booths in Uttar Pradesh used in the Parliamentary election of 2014 (140,000 booths) and the State Assembly election of 2017 (152,000 booths). We are able to link the 2014 and 2017 elections for almost 100,000

of these polling booths. The sample is however reduced to about 63,000 polling booths before merging with the NREGS data. First, we remove observations with either missing or misreported geocodes. This reduces the sample by as much as 30,000 polling booths. Second, we remove polling booths without a valid turnout rate for both genders (either below 0 or above 100). This reduces the sample further with about 6,000 polling booths. Figure A1 illustrates the Census villages included in the polling booth sample.

FIGURE A1: Map of polling booth sample



Note: The yellow areas display the Census villages included in the polling booth sample.

A.2 NREGS data

We extract data on NREGS from the *MGNREGA Public Data Portal*. This portal has information on implementation at the level of Gram Panchayats for the financial year of 2011-12 and onwards. We make use of the following variables: the number of days worked by gender, the number of workers, the number of job card applications, and the total amount disbursed to workers' bank and post office accounts.

The NREGS data provides names of districts, blocks and Gram Panchayats but does not have Census identification numbers. Our matching with the Census is therefore based on location names. We first match district and block names based on a combination of fuzzy matching and manual checking. We then match Gram Panchayat names within each district and block based on fuzzy matching.[1] In total, we are able to match the

[1]We us the Stata command `matchit`.

Census and the NREGS dataset for about 76 percent of all Gram Panchayats in Uttar Pradesh.[2] Figure A2 maps the Census villages in the NREGS sample.

FIGURE A2: Map of NREGS sample

Note: The yellow areas display the Census villages included in the NREGS sample.

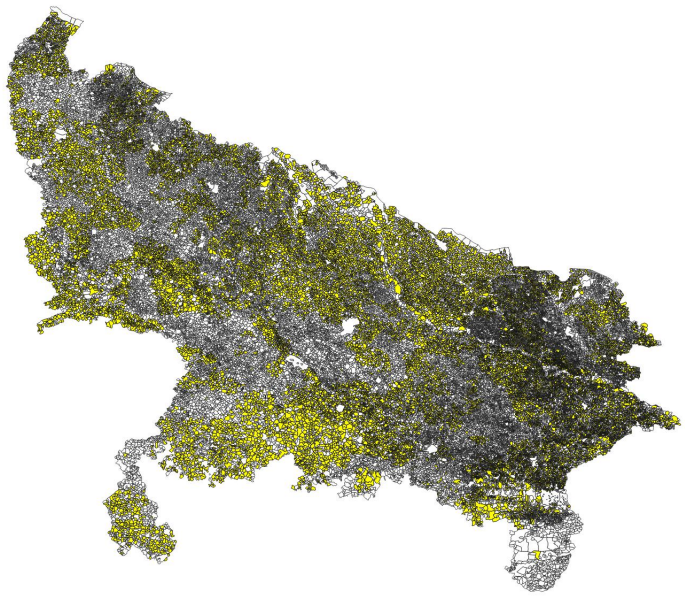
A.3 Estimation sample

The final polling booth data covers 63,414 polling booths from 26,890 Gram Panchayats, while the NREGS data covers 44,085 Gram Panchayats. The overlap of the two datasets comprises our main estimation sample, consisting of 50,490 polling booths from 21,116 Gram Panchayats (about 36 percent of all Gram Panchayats in Uttar Pradesh). Figure A3 maps this sample.

Average Gram Panchayat population in the estimation sample is somewhat higher than in Uttar Pradesh as a whole (2998 vs. 2491). This is mainly due to the polling booth data, as we show in Table A1. As a consequence, the average number of workdays is also slightly higher in the estimation sample than in the full NREGS sample (but not so in per capita terms). Electoral participation is about similar in the estimation sample and the full polling booth sample.

[2]See Asher and Novosad (2017); Gulzar and Pasquale (2017); Kjelsrud, Moene and Vandewalle (2020) for similar type of matching in the Indian context.

FIGURE A3: Map of estimation sample



Note: The yellow areas display the Census villages included in our estimation sample.

TABLE A1: Characteristics of missing observations

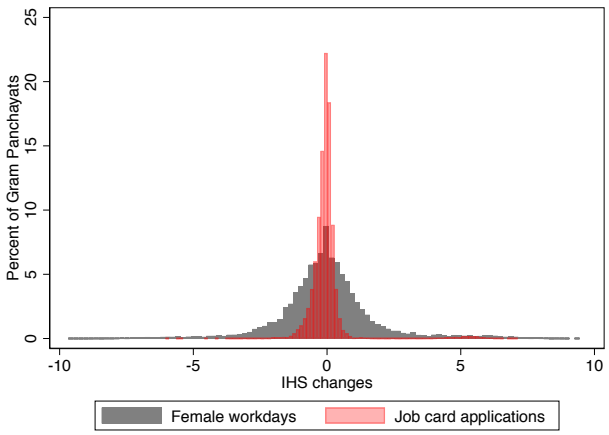
	Sample (1)	Missing observations (2)
Panel A: Population (Gram Panchayats) (*Different samples vs. Census*)		
NREGS sample	2743	2462
	N=44,085	*N=13,965*
Polling booth sample	3032	2368
	N=26,890	*N=31,160*
Estimation sample	2998	2491
	N=21,116	*N=36,934*
Panel B: NREGS workdays (*Estimation sample vs. NREGS sample*)		
Females in 2013-14	781	671
Females in 2016-17	976	841
Males in 2013-14	2693	2455
Males in 2016-17	1983	1723
	N=21,116	*N=22,969*
Panel C: Electoral turnout (percent) (*Estimation sample vs. Polling booth sample*)		
Female turnout in 2014	59.9	59.6
Female turnout in 2017	64.8	64.5
Male turnout in 2014	63.5	62.9
Male turnout in 2017	61.9	61.1
	N=50,490	*N=12,395*

B Validating the identifying assumptions

Our identification assumes that local time changes in NREGS employment are unrelated to factors determining women's voting behaviour. In this section, we validate this assumption in different ways.

We first illustrate the main identifying variation used in our estimation. The grey bars in Figure A4 show the distribution of IHS-transformed changes in female workdays, after we partial out the fixed effects. Our conjecture is that these changes are driven primarily by supply of jobs, not local demand. As a first assessment of how plausible this is, we also plot the distribution of changes in job card applications. To get work, people are required to have a job card, and hence, the number of applications can be seen as proxy for the local demand for work. Consistent with our conjecture, the number of workdays vary much more than the number of card applications. That is, actual employment, which we argue is driven mostly by availability of jobs, is much more erratic than the direct measure of demand.

FIGURE A4: Distribution of changes in female workdays and job cards applications



We provide three additional tests to validate the identifying assumption. First, we test whether changes in job card applications predict turnout within our regression framework, which we would expect if our estimates are confounded by local demand shocks. Reassuringly, we find no effect on turnout (Column 1 of Table A2). Second, we regress changes in turnout on *future* changes in NREGS (over the years 2016-17 to 2018-19) to test whether our identification picks up underlying trends in demand or supply of jobs. This does not seem to be the case (Column 2 of Table A2).

Third, we check whether time variation in employment is related to Gram Panchayat

TABLE A2: Placebo regressions

Dep. var.:	Δ Female turnout	
	(1)	(2)
ΔIHS(*Job card applications*)	0.033	
	(0.048)	
ΔIHS(*Future female workdays*)		-0.039
		(0.030)
Observations	50490	50490
R^2	0.493	0.493

All regressions include Assembly constituency times block fixed effects, and all the controls. Robust standard errors clustered at the level of the fixed effects are shown in the parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

pre-characteristics. To do so, we run the following regression:

$$\Delta\text{IHS}(Female\ workdays_{jkl}) = \gamma V_{ijkl} + \theta_{kl} + e_{ijkl}, \tag{A1}$$

where V_{ijkl} is the variable of interest (at either the Gram Panchayat or the polling booth level), and θ_{kl}, as before, represents the fixed effects. Table A3 displays the coefficient of interest, γ, for a set of variables. To facilitate the comparison across regressions, we standardise all variables in V_{ijkl} to mean zero and standard deviation one.

Panel A displays estimates for the polling booth variables. Panel B shows variables from the Socio-economic and Demographic Census, and Panel C shows variables from the Census village directory, capturing availability of publicly provided goods and services. The variables are measured as population shares of the Gram Panchayats that live in a village with the particular public good present. Finally, in Panel D we check the sample balance in terms of some additional variables, for which we do not have data for the full estimation sample: average per capita consumption from the Shrug database (Asher et al., 2019), female employment shares from the Economic Census and turnout rates from the 2012 State Assembly election.

The table suggests that changes in female workdays, at the level we are studying, are unrelated to (observed) Gram Panchayat and polling booth characteristics. We also test whether the variables in Panels A to C are jointly significant. We do this by including them in Equation (A.1), all at once. The F-test from this exercise is 0.87, and 0.89 if we also include the variables in Panel D. This implies that the listed observables are far from being jointly significant.

TABLE A3: Sample balance

	ΔIHS(*Female workdays*) (1)
Panel A: Polling booth variables 2014	
Turnout rate males	-0.002
	(0.014)
Turnout rate females	-0.002
	(0.013)
Eligible voters	0.010
	(0.011)
Hindus	0.004
	(0.014)
Muslims	0.010
	(0.018)
	N=50,490
Panel B: Census demographics 2011	
Total population	-0.002
	(0.025)
Schedule caste	-0.027
	(0.023)
Schedule tribes	-0.008
	(0.020)
Male literaters	-0.007
	(0.026)
Female literates	-0.011
	(0.025)
	N=50,490
Panel C: Census amenities 2011	
School (grade 1 to 8)	-0.021
	(0.021)
Primary health center	-0.000
	(0.022)
Electricity	-0.020
	(0.026)
Tap water	0.022
	(0.026)
Paved road	0.036*
	(0.021)
Bus, train or ferry	-0.015
	(0.023)
	N=50,490
Panel D: Other variables	
Turnout rate 2012 (booth)	0.012
	(0.017)
	N=48,972
Average per capita consumption 2013 (GP)	-0.053*
	(0.029)
	N=49,668
Female employment share (GP)	-0.006
	(0.020)
	N=48,454

Each row represent a separate regression according to (A.1). All regressions include Assembly constituency times block fixed effects. Robust standard errors clustered at the level of the fixed effects are shown in the parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

C Magnitude of the estimated effect

The program effect from Table 1 in the main paper is 0.085. This implies that a 10 percent increase in female NREGS workdays leads to a rise in female turnout of 0.0085 percentage points. At first sight, this seems like a small effect. However, the back-of-the-envelope calculation presented below suggests that it is not.

Note first that the average number of female workdays per Gram Panchayat in 2013-14 is 820 in our estimation sample. If we divide this by the average number of workdays per worker (for both genders), we get an estimate of the average number of female workers, of 28. Thus, a 10 percent increase in female workdays corresponds to about 2.8 more female workers.

We next assume that turnout among female NREGS workers is similar to the average among all females, of around 60 percent. Given this, we can scale the number and state that a 10 percent increase in workdays corresponds to an increase of 1.12 non-voting female workers (2.8×0.4). This corresponds to about 0.1151 percent of the average number of eligible female voters per Gram Panchayat.

Finally, we can compare this with the estimated treatment effect. One way of interpreting our results is thus that 7 percent (0.0085/0.1151) of the previously non-voting female workers start to vote due to the program.

D Robustness

In this section we provide robustness tests of our main findings on female turnout.

D.1 Time dynamics

We first investigate time dynamics by regressing changes in female turnout on annual (IHS-transformed) changes in female employment over the period 2012-13 to 2018-19. Table A4 provides two main take-aways. First, the estimates indicate that the effect on turnout is relatively immediate, as we only find positive coefficients for years *in-between* the two elections, and not for prior years. Second, the estimates show that changes in female turnout between 2014 and 2017 cannot be predicted by *future* changes in employment. This supplement our placebo regressions, as it suggests that our empirical setup is not confounded by underlying trends in demand or supply of jobs.

Table A4: Time dynamics

	Δ Female turnout, 2014 to 2017
	(1)
Annual changes in female workdays (IHS):	
Δ2018-19	-0.012
	(0.044)
Δ2017-18	0.005
	(0.043)
Δ2016-17	0.066*
	(0.039)
Δ2015-16	0.131***
	(0.040)
Δ2014-15	0.089***
	(0.034)
Δ2013-14	-0.014
	(0.045)
Δ2012-13	0.022
	(0.035)
Observations	50490
R^2	0.494

All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls. Robust standard errors clustered at the level of the fixed effects are shown in the parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

D.2 Alternative functional forms

In Table A5 we test how sensitive our results are to alternative functional forms. In the first column, we regress changes in female turnout on log-transformed changes in workdays. The coefficient can be compared directly with our estimate from Table 1 in the main paper. Hence, the log-transformation suggests a somewhat larger effect on turnout (0.096 vs. 0.085).

In the second column, we use level changes in the number of workdays. As this specification is likely to be sensitive to outliers, we run an additional regression – shown in the third column – where we remove observations with values +/− five standard deviations from the mean. The average number of workdays in the estimation sample is about 820. Thus, a 10 percent increase in workdays from this level implies a rise in the turnout rate of 0.0096 percentage points, according to the coefficient in Column (2), and a rise of 0.0121 percentage points, according to the coefficient in Column (3). Again, these magnitudes are slightly larger than our main estimates.

Table A5: Alternative functional forms

	Δ Female turnout		
	(1)	(2)	(3)
$\Delta\text{Log}(Female\ workdays + 1)$	0.09591***		
	(0.02750)		
$\Delta Female\ workdays$		0.00012***	0.00015***
		(0.00004)	(0.00006)
Observations	50490	50490	50257
R^2	0.494	0.493	0.493
Removing outliers	No	No	Yes

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls. In Column (3) we remove observations with female workdays higher/lower than mean +/− 5 standard deviation.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

D.3 Alternative measures of NREGS

We next investigate the sensitive to alternative measures of local program implementation. In the first column of Table A6 we regress female turnout on *male* workdays, and in the second column on both male *and* female workdays. The estimates suggest that our results on female turnout are driven primarily by female employment. For completeness, we repeat the latter exercise for male turnout. We find no significant effects in this

regression, as shown in the third column.

In Table A7, we regress female turnout on i) changes in the number of NREGS workers, and ii) changes in the amount disbursed to workers' bank and post accounts. Note that for these measures we only have data for both genders combined. Yet, we still find highly significant effects on female turnout. In the final column we show that this also applies for total workdays.

TABLE A6: Alternative measures: female and male workdays

	Δ Female turnout		Δ Male turnout
	(1)	(2)	(3)
ΔIHS(*Female workdays*)		0.078*	0.004
		(0.043)	(0.042)
ΔIHS(*Male workdays*)	0.074***	0.012	0.032
	(0.027)	(0.047)	(0.046)
Observations	50490	50490	50490
R^2	0.493	0.493	0.484

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

TABLE A7: Alternative measures: workers, pay and workdays (both genders)

	Δ Female turnout		
	(1)	(2)	(3)
ΔIHS(*Workers*)	0.116***		
	(0.043)		
ΔIHS(*Pay*)		0.085***	
		(0.024)	
ΔIHS(*Workdays*)			0.077***
			(0.026)
Observations	50490	50490	50490
R^2	0.493	0.493	0.493

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

D.4 Alternative coding choices

Finally, we investigate the sensitive of our results to a set of coding choices. Estimates are shown in Table A8.

In the construction of the NREGS dataset we link observations to the Census based on fuzzy matching of Gram Panchayat names, and by using a particular threshold to define acceptable matches. More concretely, we measure the similarity of two matched names based on the so-called Jaccard index. The index ranges from 0 to 1, and is defined as follows: $m/\text{sqrt}(s1 * s2)$, where m is the amount of grams matched and $s1$ and $s2$ are the amount of grams in the two Gram Panchayat names. In the main sample we use a threshold of 0.5. Here we test whether our results survive the use of higher thresholds. The regressions shown in Columns 1 and 2 are based on thresholds of 0.6 and 0.75, respectively. The use of these stricter thresholds reduces the sample size, but as can be seen, it does not affect our main findings, except to increase the point estimates somewhat. In Column 3, we restrict the sample to fully matched Gram Panchayat names. This reduces the sample by around 60 percent, and hence, we lose a lot of precision. Still, the point estimates is almost exactly the same as our main estimate.

The remaining of the table provides two additional robustness tests. First, we use the alternative turnout rate discussed in Section A.1. This somewhat increases the magnitude of the estimated effect. Second, we collapse the sample to the level of Gram Panchayats. Again, this alternative coding choice does not affect our main finding.

TABLE A8: Alternative coding choices

	Δ Female turnout				
	Min match score> .60	Min match score> .75	Full match	Alternative turnout rate	Collapsed to GPs
	(1)	(2)	(3)	(4)	(5)
ΔIHS(*Female workdays*)	0.105***	0.094***	0.081*	0.117***	0.089***
	(0.027)	(0.033)	(0.049)	(0.027)	(0.024)
Observations	46579	35432	20693	40204	21116
R^2	0.492	0.498	0.512	0.500	0.569

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls. In Column (5), the booth level controls are collapsed to the GP level.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

E Effects on voting patterns and concentration

One possible mechanism for the estimated effect of NREGS on voter turnout is program satisfaction. We test for this by studying voting patterns. The Susewind (2016) database includes data on vote shares for different political parties, but not by gender. Because of this, we first document that the impact of female workdays on female turnout is strong enough to move overall turnout in the sample for which we have vote shares (Column 1 in Table A9).

If the program induces people to vote because they want to award the politicians that gave them NREGS, we would expect to not only see effects on turnout but also on the composition of the votes casted. In Column 2 of Table A9 we test whether female employment affects vote shares for the parties of the local MLAs, and in Column 3, we test for effects on voting for the parties of the local MPs. In the subsequent columns we study voting for three particular political parties: in Column 4, voting for the majority party of the State Assembly in Uttar Pradesh (2012-2017), the *Samajwadi Party* (SP); in Column 5, voting for the majority party in the National Parliament (2014-2019), the *Bharatiya Janata Party* (BJP); and in Column 6, voting for the Indian National Congress (INC). INC was a relatively minor party in Uttar Pradesh during our study period, but still relevant as NREGS often is seen as the flagship program of INC (Gupta and Mukhopadhyay, 2016; Zimmermann, 2020).

We do not find significant effects of female employment in any of the regressions. Because of this, we find it unlikely that our findings on electoral participation are caused by program satisfaction alone. Still, even if we do not find any effects on the aggregate vote shares it could still be the case that NREGS causes women to overwhelmingly vote for a single party *at the local level* but that such differences cancel out in the aggregate. This could for instance happen if different political parties use intermediaries to mobilize female workers at the NREGS worksites.

To test for this, we calculate the concentration of party vote shares at the polling booth level. We use two commonly used measures: the effective number of parties (ENOP) and one minus the Herfindahl-Hirschman index. The ENOP, developed by Laakso and

Taagepera (1979), is measured as follows:

$$ENOP_{ip} = \frac{1}{\sum_{p=1}^{n} s_{ip}^2},$$

where s_{ip} is the vote share of party p at polling booth i, while the Herfindahl-Hirschman index is calculated as:

$$100 - HHI_{ip} = 1 - \sum_{p=1}^{n} s_{ip}^2$$

We use these two measures of the vote share concentration in the regressions shown in Table A10. The coefficients of NREGS workdays are negative, but their magnitudes are small, and they are far from being statistical significant. Thus, this result is inconsistent with a story of block voting and mobilized political participation. In combination with the other evidence provided in the main paper, the result is instead consistent with increased autonomous political participation, which is important for the normative interpretation of our findings.

TABLE A9: Total turnout and voting patterns

		Δ Vote shares for political parties				
Dep. var.:	Δ Total turnout	Current MLAs	Current MPs	SP	BJP	INC
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIHS(*Female workdays*)	0.057**	-0.027	0.036	0.003	0.037	-0.034
	(0.023)	(0.037)	(0.035)	(0.036)	(0.036)	(0.026)
Observations	44874	44874	44874	44874	44874	44874
R^2	0.527	0.718	0.755	0.724	0.737	0.707

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls. The regressions in Column (2) to Column (6) additionally control for vote shares of the relevant political parties in the 2012 and 2014 election.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

TABLE A10: Party vote share concentration

Dep. var.:	Δ ENOP (1)	Δ (100-HH) (2)
ΔIHS(*Female workdays*)	-0.001	-0.041
	(0.002)	(0.033)
Observations	50453	50453
R^2	0.590	0.338
Dep. var mean	-0.011	-0.168

Robust standard errors clustered at Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, polling booth and Gram Panchayats controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

F The Prillaman (2021) dataset

In this section we provide more details on the analysis based on the Prillaman (2021) dataset. The survey data was collected in May to July 2016 and covers a total of 2645 women and 965 husbands from 152 villages in Madhya Pradesh. Importantly for us, the dataset provides village census identifiers. We are therefore able to merge it with the battery of administrative data used in our other analysis. In particular, we make use of the Gram Panchayat level data on NREGS implementation and the 2011 Census for village characteristics.

F.1 Regressions based on time variation

Our main analysis is based on time variation in administrative data on voter turnout and NREGS employment within Gram Panchayats in Uttar Pradesh. In the main paper, we present a similar exercise using the survey data from Madhya Pradesh. Below we provide more details on this.

The analysis is based on self-reported turnout in the local election in 2014-15 and the state election in 2013. We collapse this to the village level (by calculating the average turnout among females for each election), to make the analysis as similar as possible to our main specification. We then regress changes in turnout on changes in female workdays between the financial years 2012-13 and 2013-14. As in our main specification, we add fixed effects at the level of block×State Assembly constituency, and the full set of village controls. We also use the following individual controls, averaged to the village level: highest education level, schedule caste, schedule tribe, hindu and age. We cluster the standard errors on Gram Panchayats, since we only have 22 fixed effects (block×State Assembly constituency).[3]

Doing all of this, we find a strong positive effect of female workdays on voting, as reported in the main paper and reproduced in Column 1 of Table A11. How does this effect compare with our estimates for Uttar Pradesh? The point estimate is about 12-13 times as large as the point estimate from our main analysis. Note however that a percentage increase in NREGS implies a much larger *absolute* increase in this case. For Uttar Pradesh, we calculate that a 10 percentage increase in NREGS workdays corresponds to

[3]The results are not sensitive to this choice.

about 2.8 female workers per Gram Panchayat (see Appendix C). The similar number in Madhya Pradesh is 22.4. If we take this into account, the two estimates are broadly in line.

Table A11: Turnout and NREGS

Dep. var.:	ΔFemale Turnout			ΔMale Turnout
	(1)	(2)	(3)	(4)
ΔIHS(*Female workdays*)	1.069***			
	(0.403)			
ΔIHS(*Job cards applications*)		1.135		
		(2.748)		
ΔIHS(*Future workdays*)			-0.656	
			(0.921)	
ΔIHS(*Male workdays*)				-0.180
				(0.226)
Observations	152	152	152	149
R^2	0.881	0.871	0.873	0.811

Robust standard errors clustered on Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, and the full set of controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

In the rest of Table A11 we present three placebo regressions similar to those presented in the main paper. In the first placebo, we replace changes in workdays with changes in the number of job card applications. The point estimate is about the same as for workdays, but very imprecisely estimated and far from being statistically significantly different from zero (Column 2). We next test whether changes in future workdays, over the years 2014-15 to 2015-16, predicts changes in turnout. It does not (Column 3). Finally, we run the specification for husbands, and find no effects of NREGS on voting (Column 4).

F.2 Regressions based on cross-sectional variation

For the outcomes related to non-electoral political participation and social networks we do not have time variation. We therefore have to rely on a cross-sectional analysis. Below we present a more exhausted list of outcomes than in the main paper. In particular, we present all outcomes from Tables 2, 3 and 5 in Prillaman (2021). The estimation results are presented in Tables A12, A13 and A14 below. As before, we include block×State Assembly constituency fixed effects, the full set of village controls and the following individual controls: highest education level, schedule caste, schedule tribe, hindu and dummies for five-year age groups.

In Table A12 we show a positive correlation with voting in the latest local elections before the survey (2014-2015) but there is no effect on self-reported turnout in the state election 2013. We are not worried about these results as we show in the main body of the paper that we can identify effects in this data using an empirical specification that is more closely related to our preferred specification. In addition, self-reported data on turnout is not as good as administrative data, especially due to recall bias when going further back in time. The table also shows that NREGS affects the nonvoting participation index, whether or not women attend campaign events, whether or not women are motivated for campaigns, and whether or not they attend meetings of political parties.

In Table A13 we further see that there are effects on the number of friends, number of female friends, number of people women discuss politics with, and political knowledge (as measured by the information index). Finally, Table A14 shows negative effects on expenditures and positive effects on employment.

TABLE A12: Political participation (Outcomes from Table 2 in Prillaman, 2021)

	Coefficient	Mean dep.var
	(1)	(2)
Voted in local election	0.019*	0.942
	(0.011)	
Voted in state election	-0.013	0.782
	(0.024)	
Nonvoting participation index	0.134*	0.864
	(0.076)	
Attend village assembly meeting	0.021	0.273
	(0.023)	
Contact Panchayat for govt. benefit	0.024	0.152
	(0.017)	
Submit application to Panchayat for services	-0.004	0.125
	(0.016)	
Contact block for govt. benefit	0.010	0.046
	(0.008)	
Submit application to block for services	0.010	0.044
	(0.010)	
Attend campaign event	0.022*	0.079
	(0.013)	
Motivate for campaign	0.031**	0.116
	(0.015)	
Attend party meeting	0.019***	0.029
	(0.006)	
Observations	2645	

Each row represent a separate regression, where the listed variable is the dependent variable and the coefficient is the estimated effect of female NREGS workdays in 2015-16 over the female population (IHS-transformed). Robust standard errors clustered on Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, and the full set of controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

TABLE A13: Social networks (Outcomes from Table 3 in Prillaman, 2021)

	Coefficient	Mean dep.var
	(1)	(2)
# Friends in village	0.418***	2.593
	(0.128)	
# Female friends in village	0.398***	2.530
	(0.116)	
Would go to friends for support	-0.016	0.592
	(0.020)	
# Discuss important matters with	0.038	1.213
	(0.060)	
# People visit in free time	0.078	1.169
	(0.058)	
# Discuss politics with	0.104*	1.028
	(0.059)	
Discusses politics with family	0.009	0.268
	(0.018)	
Discusses politics with friends	0.008	0.248
	(0.020)	
Mobility index	0.123	3.496
	(0.078)	
Information index	0.172*	4.594
	(0.091)	
Political efficacy index	-0.035	1.547
	(0.047)	
Confidence index	-0.002	1.543
	(0.045)	
Observations	2645	

Each row represent a separate regression, where the listed variable is the dependent variable and the coefficient is the estimated effect of female NREGS workdays in 2015-16 over the female population (IHS-transformed). Robust standard errors clustered on Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, and the full set of controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

TABLE A14: Resources and Intra-household Bargaining (Outcomes from Table 5 in Prillaman, 2021)

	Coefficient	Mean dep.var
	(1)	(2)
Assets index	0.038	1.650
	(0.066)	
Consumption index	-0.001	4.102
	(0.069)	
Monthly household expenditure	-238.627**	3510.974
	(117.865)	
Income sufficiency	0.001	0.616
	(0.019)	
Food security	-0.027	0.249
	(0.017)	
Time to save Rs 400	0.035	3.411
	(0.091)	
Decision-making index	0.131	8.165
	(0.123)	
Whom to vote for	0.003	0.860
	(0.013)	
Gram Sabha attendance	0.011	0.814
	(0.018)	
Permission index	0.003	4.221
	(0.063)	
Bargaining power index	0.059	2.078
	(0.053)	
Personally holds cash	-0.003	0.511
	(0.021)	
Personally has bank account	0.016	0.686
	(0.024)	
Personally owns assets	-0.002	0.296
	(0.019)	
Personally owns land	0.004	0.093
	(0.010)	
Employed in past year	0.044*	0.490
	(0.026)	
Domestic violence index	0.002	0.408
	(0.029)	
Verbal abuse index	-0.003	0.317
	(0.029)	
Observations	2645	

Each row represent a separate regression, where the listed variable is the dependent variable and the coefficient is the estimated effect of female NREGS workdays in 2015-16 over the female population (IHS-transformed). Robust standard errors clustered on Gram Panchayats in the parentheses. All regressions include Assembly constituency times block fixed effects, and the full set of controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

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