Female employment and voter turnout - Evidence from India*

Anders Kjelsrud[1] and Andreas Kotsadam[2]

[1]Oslo Business School, OsloMet

[2]Ragnar Frisch Centre for Economic Research

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Abstract

Previous research on the effects of employment on voter turnout yields mixed results. Combining data from the largest workfare program in the world with data from over 50,000 Indian polling stations we show that increased employment substantially increases female turnout. Mechanism tests suggest the results are driven by employment rather than income and program satisfaction. In particular, we find increases in the number of friends, discussions of politics with more people, and increased knowledge of politics. We also find effects on non-electoral political participation and we argue that the effects we identify are driven by autonomous political participation.

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1 Introduction

Inequality in voting turnout across genders implies inequality in political representation. This represents a democratic problem as men and women have different political preferences (see e.g. Chattopadhyay and Duflo, 2004), and as inequalities in political participation may reproduce other types of inequalities and create a mismatch between policies and actual social preferences (Lijphart, 1997). Women's lower political participation may also prevent them from gaining political knowledge, skills and political networks, making inequality in participation self-sustaining as politicians may target the more politically salient men (Bleck and Michelitch, 2018; Prillaman, 2021).

Female employment is thought to increase turnout and political participation more broadly via several channels (Isaksson, Kotsadam and Nerman, 2014; Robinson and Gottlieb, 2019). It directly increases incomes, which might not be a binding constraint for most types of participation but it may be important through increased bargaining power in the household. Also, employment often leads to improved civic skills, political knowledge, and access to networks. On the other hand, employment is time consuming, and hence, the effect on participation could go in the opposite direction (Schlozman, Burns and Verba, 1999). Aalen et al. (2021) also show that poor employment conditions can actually decrease political efficacy.

In this paper, we study the effect of women's employment on women's turnout in India. We identify the relationship by exploiting variation in the availability of jobs in the *National Rural Employment Guarantee Scheme* (NREGS). NREGS is the largest workfare program in the world, employing 40 to 50 million rural households every year. We focus on the largest state in India, Uttar Pradesh, with a population of more than 200 million people.

Our main finding is that the program increases turnout, and we argue that the effect is caused by increased employment rather than other program induced changes or omitted variables. In particular, we find no effects on men, whom are much more likely to work regardless of NREGS; no effects on party choice, which would be expected if the program increased turnout via pork barrel spending; and no effects on the local concentration of party vote shares, which would be expected if the effect was driven by block voting and mobilization of women voters.

We do not believe that the effects of employment are driven merely by income increases, for the following reasons: i) the total number of days worked in NREGS are capped, and in our sample, individuals in the program only work around 30 days per year on average; ii) we find larger effects in areas where the program has the largest effects on whether or not women are working, rather than in areas where it is more likely to only increase income; iii) NREGS work is conducted in groups where women work together with other women, often from different castes, communities and neighborhoods, which directly increases their networks (Jenkins and Manor, 2017; Khera and Nayak, 2009).

We provide further support for this interpretation using data collected by Prillaman (2021) in the neighboring state of Madhya Pradesh. Using this data, we show that NREGS employment leads to a larger number of friends in the village, a larger number of people whom women discuss politics with, and to greater political knowledge. Interestingly, we find no effects on bargaining power within the household. We also show that NREGS seems to increase meeting attendance and non-electoral political participation more broadly. In combination with the evidence against block voting, these findings are therefore most consistent with increases in autonomous political participation, rather than elite induced or mobilized participation. This is important normatively, particularly in developing country settings, and particularly among women where gendered social pressures and norms are strong, as autonomous political participation has the potential for furthering women's agency and making preferences of the electorate more aligned with those of the population (Bleck and Michelitch, 2018; Collier, 1982; Giné and Mansuri, 2018).

The conclusion from our quantitative mechanism tests is consistent with qualitative evidence. Olausson (2017) interviewed women in Andhra Pradesh, which is another neighboring state, and found for instance one women stating: *"Before NREGA I never voted and I am very proud and empowered to be able to do this now"* (p.33); and another women explaining: *"I have become more politically aware now as we discuss politics when we work in NREGA. Twenty people discuss politics and village issues. I believe this has influenced my political involvement. NREGA creates a platform where we can discuss village politics while working"* (p.34). In many ways, the NREGS worksites have similarities with the so-called Self-Help Groups (SHGs) in India, which Prillaman (2021) shows lead to higher political participation. Like the SHGs, the NREGS worksites bring together women with shared interest, which may foster discussions on politics and on other issues, and generate capacity for collective action, for instance through collective protests when wages are withheld. In patriarchal settings where women otherwise have few social ties (Kandpal and Baylis, 2019), such networks may be difficult to find.

Our paper contributes to the small but growing literature on the causal effects of employment on turnout (see Margalit, 2019, for an overview). Previous literature has mostly used trends in general employment to identify effects and the results are overwhelmingly from developed countries. We specifically contribute by estimating the effects of an actual policy, which increases the policy relevance of our findings. Our tests of mechanisms are also more extensive than in previous literature, which has not separated out income, knowledge, and network effects of employment. In the only study with a design to identify causal effects outside of Europe or the US, Aalen et al. (2021) find that factory employment in autocratic Ethiopia has no effect on turnout intentions but that it lowers participation in community meetings. Aalen et al. (2021) argue that their negative finding is due to the extremely poor working conditions in their setting. Our paper contributes to the understanding of scope conditions, in particular considering that we find positive effects of employment in a relatively poor country with low gender equality in general. One possible interpretation is therefore that the work environment has to be minimally hospitable for any positive effect on turnout to materialize. Finally, we are able to study turnout over a relatively long time period, which is important as the effects of employment have previously been found to be temporary.

2 The National Rural Employment Guarantee Scheme

NREGS was rolled out in rural India during the years 2006 to 2008 and is now the world's largest workfare program, employing 40 to 50 million rural households each year. Below we emphasize two characteristics of the program that are particularly relevant for our later explorations.

The first characteristic is the high level of female participation. In many Indian states, more than half of the NREGS jobs are taken up by women (Ravi and Engler, 2015). This contrasts sharply with the regular labour market where male workers are in overwhelming majority (Klasen and Pieters, 2015). The program has explicit quotas for women and there are several other program features that are attractive to female workers. Equal wages for men and women is one such feature. Since women typically are paid less than men in other types of jobs, equal wages imply that NREGS is relatively better paid for women. Short work distance is another. The worksites are most often located within workers' own village, and this is likely to be important for women combining household work with paid work. Relatedly, work hours in the program are clearly regulated and the worksites have child care facilities.

Khera and Nayak (2009) describe how these factors, and the fact that women work together in groups, help make the public jobs "socially acceptable". As such, NREGS is likely to provide the first real work opportunity for many women in rural India. The pattern in Figure 1 is consistent with this assertion. Based on the *NSS Employment-Unemployment survey* from 2011-12, we show that more than 80 percent of the female NREGS workers in Uttar Pradesh did not have any other type of paid work. This suggests that they would not have been working in the absent of NREGS, and also, that the program plausibly induces significant behavioral changes.

The second important characteristic is the large *variation* in NREGS. In the empirical analysis we explore changes in the availability of jobs over time. In principle, the variation should be driven completely by demand for work, as every rural household is legally entitled to request 100 days of work each year. Still, mounting evidence suggest that most of the variation in NREGS is due to unmet demand for employment (Dutta et al., 2014). In practice, the program is therefore best described as supply constrained.

Several factors are likely to be decisive for the program implementation at the local level. The fiscal and administrative capacity of state and lower level governments is one important factor.[1] The fact that the poorest states in India, where demand expectedly should be highest, consistently have supplied fewer NREGS jobs than the richest states is consistent with this (Imbert and Papp, 2015). Previous research suggest that the motivation and incentives of politicians and bureaucrats also matter. This strand of research has focused on the allocation of funds across either states, districts or development blocks, highlighting the role of state-level politicians and block-level bureaucrats (see e.g. Gulzar and Pasquale, 2017; Gupta and Mukhopadhyay, 2016). In our empirical analysis we utilize variation at the lower level of Gram Panchayats. Thus, our estimation abstracts from the possible strategic allocation of funds across these higher administrative levels.

3 Empirical approach

We use three main data sources to study the relationship between employment and voter turnout. Firstly, we use the 2001 Census village map from the InfoMap. This map provides boundaries of every Census village, which facilitates the merging of other datasets with geographical identifiers. In addition, we make use of the 2011 Census to obtain Gram Panchayat characteristics. Secondly, the Susewind (2016) dataset provides information on key characteristics of the polling booths in Uttar Pradesh, including GPS coordinates. As every eligible voter in India has to vote at one specific polling booth, we can credibly calculate turnout rates at this level. Thirdly, we extract Gram Panchayat level data on NREGS from the MGNREGA Public Data Portal, which we link to the Census based on fuzzy matching on location names.

[1] The central government provides most of the funding, but local governments still have to pay a share of the project costs and some of the administrative costs.

Overall, this gives us an estimation sample of 50,490 polling booths from 21,116 Gram Panchayats (about 36 percent of all Gram Panchayats in Uttar Pradesh). We provide more details on the data construction in Appendix A.

We capture the effect of employment on turnout by using *time* variation in the number of NREGS jobs within Gram Panchayats. We regress changes in female turnout between the elections in 2014 and 2017 on changes in female workdays between the financial years 2013-14 and 2016-17, adding block fixed effects constructed within each State Assembly constituency (as some blocks are split between different State Assembly constituencies).[2] The specification can thus be written as follows:

$$\Delta Female\ turnout_{ijkl} = \beta \Delta \text{IHS}(Female\ workdays_{jkl}) + X1'_{ijkl} + X2'_{jkl} + \theta_{kl} + e_{ijkl}, \qquad (1)$$

where the subscript i denotes polling booths, j denotes Gram Panchayats, k denotes development blocks and l denotes State Assembly constituencies. Our main NREGS measure captures changes in the inverse hyperbolic sine (IHS) of female workdays. The β-coefficient in (1) can be interpreted in the same way as with a log-transformation, but unlike the log, the IHS is defined for the value of zero (Burbidge, Magee and Robb, 1988). We also include a set of polling booth level controls measured in 2014 ($X1'_{ijkl}$): male and female turnout rates, total number of eligible voters, number of eligible Hindu and Muslim voters; and a set of Gram Panchayat-level controls from the 2011 Census ($X2'_{jkl}$): total population; the number of Schedule castes, Schedule tribes, literate men and literate women; availability of public schools, government health clinics, electricity, tap water, paved roads and public transport. The fixed effects for blocks$\times$State Assembly constituencies are denoted by θ_{kl}.

A causal interpretation of the β-coefficient requires that the local variation in NREGS employment is orthogonal to factors determining voter turnout. We believe this is plausible given that our identifying variation is within small geographical areas and given that employment in the program is determined primarily by constrained supply. This is particularly so for women, we believe, because female participation is likely to depend on work being provided close to residence. We provide an extensive validation of the identifying assumption in Appendix B.

[2]The election in 2014 was for the national parliamentary, while the election in 2017 was for the State Assembly, which is analogous to the national parliament but at the state level.

4 The effect of employment on turnout

In this section we present our main results. We first estimate (1) without any of the controls, except the fixed effects. The impact of female workdays on female turnout is positive and highly significant (Column 1 of Table 1). We then add the polling booth and Gram Panchayat controls (Columns 2 and 3). This has barely any impact on the point estimate, but it increases R-squared and the precision of the estimates.[3] The magnitude of the effect is considerable. By scaling the coefficient, we show that the effect implies that about 7 percent of the female NREGS workers *that previously did not vote*, would start to vote due to the workfare program (see Appendix C). Thus, the estimated effect is both statistically and economically significant. In Appendix D, we show that this finding is robust to alternative specifications and coding choices.

How should we interpret the effect? Previous studies have found that policies that increase peoples' incomes, such as cash transfers (Pop-Eleches and Pop-Eleches, 2012) and foreign aid (Knutsen and Kotsadam, 2020), increase turnout and in particular voting for the incumbent. In our case, however, we find no effects on voting *patterns* (see Appendix E). It thus seems implausible that the effect on turnout stems from program satisfaction and from rewarding politicians for providing goods. Similarly, we find no effects on the local *concentration* of party vote shares (again see Appendix E), which we would expect if the effect was caused by targeting of female workers by political parties, for instance at the NREGS worksites. This result is therefore inconsistent with block voting being the key mechanism. Nor do we think the effect is caused by higher incomes, as the income gains, after all, are modest. In our sample, the average number of workdays per NREGS worker, *per year*, is only 30. Using the Indian Human Development Survey from 2011-2012, we calculate that the median female NREGS worker in Uttar Pradesh earns an amount equal to just 5 percent of total household income.

Instead we believe that one key mechanism is a network effect, linked to how NREGS induces women to work, and thereby, to spend time outside their household. This move into the public sphere might in itself improve self-confidence, raise aspirations and change views on what women can and cannot do – including their views on political involvement. The *way* the worksites are organized may also facilitate political awareness and provide an (unusual) arena to meet new people.

[3] It is especially the lagged turnout variables (for men and women) that increase precision, as can be seen by comparing Columns 2 and 3. The fact that the coefficient barely changes once we control for female turnout in 2014, which essentially is a lagged dependent variable, also suggests that the so-called Nickell bias (Nickell, 1981) is of little empirical relevance in our setting.

We conduct several (indirect) tests of mechanisms in our setting. Our proposed mechanism implies that the impact of NREGS should be smaller on women that already have work in the regular labor market. We test this implication using data from the Economic Census of 2013, which provides a full enumeration of all non-farm establishments. We calculate the female worker share at the block level and interact this with female NREGS workdays. To ease interpretation, we standardize the worker share to mean zero and standard deviation one. We find that the effect of NREGS is highly dependent on the level of female employment outside the work program (Column 4 in Table 1). As an alternative specification, we also interact changes in female workdays with binary variables for quartiles of the worker share variable (Column 5). The effect in the 25 percent of areas where most women are working is significantly smaller.[4] Similarly, the mechanism should imply a smaller effect on men's turnout, for the following two reasons. First, NREGS provides a weak signal for whether or not men are working, since they are likely to have additional paid work (see Figure 1). Second, men are much less constrained than women and they are likely to have a larger network regardless of their labor force participation. We test this by estimating (1) using male turnout as the outcome (Columns 6 and 7), and find much smaller effects than for female turnout.

We provide further support for the network interpretation using data collected by Prillaman (2021). This dataset is from 2016 and covers 152 villages in the neighboring state of Madhya Pradesh, which we merge with our administrative data on NREGS employment (see Appendix F for more details on the data and for additional analyses). First, using an empirical setup similar to our main specification above and women's self-reported voting turnout in the state election in 2013 and the local (Panchayat) election in 2014-2015, we find sizeable effects of NREGS employment on voting (Column 1 in Table 2). Given that the level of NREGS employment is much higher in Madhya Pradesh the point estimate is broadly consistent with our main estimates.

More importantly, the Prillaman (2021) dataset allows us to investigate the effects of female employment on non-voting political participation, knowledge, and on social networks. We are however only able to do this in the cross-section, which implies that the analysis should be seen as somewhat suggestive. We first show that the number of female workdays per capita in 2015-2016 predicts whether females in the 2016-survey report any paid work during the last year (Column 2 in Table 2). We next document that NREGS seems to increase the number of friends women have in the village (Column 3); the number of people they discuss politics with (Column 4); their political knowledge, as measured by an "Information index" (Column

[4] Adding terms we note that the effect is not statistically significantly negative in the fourth quartile.

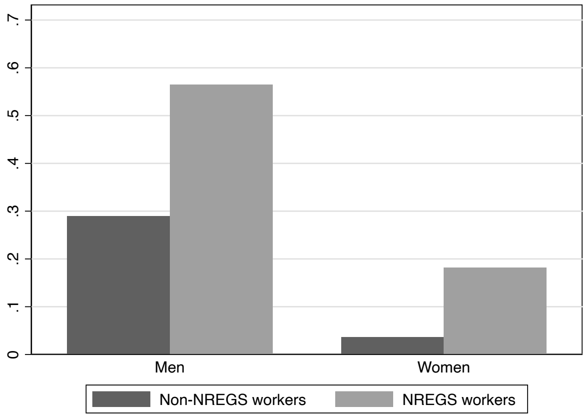
5); and their non-electoral political participation, as measured by a "Nonvoting participation index" (Column 6). These results show that networks, as well as knowledge, are important mechanisms and they provide additional evidence suggesting that the effects of employment on turnout are driven by autonomous political participation.

5 Conclusion

Combining data from the largest workfare program in the world with data from over 50,000 Indian polling stations, we find that policy-induced changes in employment substantially increase female turnout. A series of tests make us confident that the effects we identify stem from employment rather than from rewarding politicians for providing goods. In particular, we find no effects on party choice, political fragmentation, or incumbency support.

Our results show that policy and employment are able to increase female turnout, which is especially important given that men and women have been shown to have different political preferences in India (e.g. Chattopadhyay and Duflo, 2004). This is also important as the effects of employment are generally unclear and as there is a need for concrete policy advice on how to increase turnout. We hope that future studies will continue to investigate the relationship between employment and turnout in other settings so that we can reach a better understanding of the scope conditions for the effects of employment on political participation. A particularly useful endeavor would be to explicitly test for the moderating role of working conditions. We also urge future studies to investigate the effects of employment for different types of individuals, in particular for individuals of different gender and caste.

Figure 1: Employment shares outside NREGS



Note: The figure is based on data from the *NSS Employment-Unemployment survey* from 2011-12, and is restricted to respondents from Uttar Pradesh.

Table 1: NREGS employment and voter turnout

Dep. var.:	Δ Female turnout					Δ Male turnout	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔIHS($Female\ workdays$)	0.087***	0.081***	0.085***	0.078***	0.126***	0.024	
	(0.030)	(0.030)	(0.025)	(0.025)	(0.043)	(0.025)	
ΔIHS($Male\ workdays$)							0.035
							(0.027)
ΔIHS($Female\ workdays$)				-0.071***			
× female worker share (std)				(0.023)			
ΔIHS($Female\ workdays$)					0.048		
× female worker share, quartile=2					(0.066)		
ΔIHS($Female\ workdays$)					-0.042		
× female worker share, quartile=3					(0.067)		
ΔIHS($Female\ workdays$)					-0.191***		
× female worker share, quartile=4					(0.068)		
Observations	50490	50490	50490	50007	50007	50490	50490
R^2	0.167	0.174	0.493	0.494	0.495	0.484	0.484
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Lagged turnout	No	No	Yes	Yes	Yes	Yes	Yes
Dep. var mean	4.944	4.944	4.944	4.944	4.944	-1.668	-1.668

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. The voting variables capture changes in turnout between the 2017 and 2014 elections, while the NREGS variables capture changes in workdays between 2013-14 and 2016-17.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table 2: Regressions based on Prillaman (2021) dataset

Dep. var.:	ΔFemale Turnout	Worked last year (0-1)	#Friends in village	#Discuss politics with	Political knowledge (0-9)	Nonvoting partici-pation (0-8)
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIHS($Female\ workdays$)	1.069**					
	(0.494)					
IHS($Female\ workdays, per\ capita$)		0.044*	0.418***	0.104*	0.172*	0.134*
		(0.026)	(0.128)	(0.059)	(0.091)	(0.076)
Observations	152	2645	2645	2645	2645	2645
R^2	0.881	0.096	0.051	0.132	0.166	0.100
Dep.var mean	17.016	0.490	2.593	1.028	4.594	0.864

All regressions include Assembly constituency times block fixed effects. Robust standard errors clustered on Gram Panchayats are shown in the parentheses. The ΔIHS-variable captures Gram Panchayat level changes in workdays between 2012-13 and 2013-14, while the IHS-variable captures workdays in 2015-16 divided by the female population. The regression in the first column is collapsed to the village level. All regressions include the full set of village controls, and a set of individual controls (averaged to the village level in the first column).
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

References

Aalen, Lovise, Andreas Kotsadam, Janneke Pieters and Espen Villanger. 2021. "Jobs and political participation. Evidence from a Field Experiment in Ethiopia." *Mimeo* .

Asher, Sam and Paul Novosad. 2017. "Politics and Local Economic Growth: Evidence from India." *American Economic Journal: Applied Economics* 9(1):229–273.

Asher, Sam, Tobias Lunt, Ryu Matsuura and Paul Novosad. 2019. "The Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG)." Working paper.

Bleck, Jaimie and Kristin Michelitch. 2018. "Is womens empowerment associated with political knowledge and opinions? Evidence from rural Mali." *World Development* 106:299–323.

Burbidge, John B., Lonnie Magee and A. Leslie Robb. 1988. "Alternative Transformations to Handle Extreme Values of The Dependent Variable." *Journal of the American Statistical Association* 83(401):123–127.

Chattopadhyay, Raghabendra and Esther Duflo. 2004. "Women as Policy Makers: Evidence from a Randomized Policy Experiment in India." *Econometrica* 72(5):1409–1443.

Collier, Ruth Berins. 1982. *Regimes in Tropical Africa Changing Forms of Supremacy, 1945-1975*. University of California Press. Berkeley, CA.

Dutta, Puja, Rinku Murgai, Martin Ravallion and Dominique Van de Walle. 2014. *Right to Work? Assessing India's Employment Guarantee Scheme in Bihar*. The World Bank.

Giné, Xavier and Ghazala Mansuri. 2018. "Together we will: experimental evidence on female voting behavior in Pakistan." *American Economic Journal: Applied Economics* 10(1):207–35.

Gulzar, Saad and Benjamin J. Pasquale. 2017. "Politicians, Bureaucrats, and Development: Evidence from India." *American Political Science Review* 111(1):162–183.

Gupta, Bhanu and Abhiroop Mukhopadhyay. 2016. "Local Funds and Political Competition: Evidence from the National Rural Employment Guarantee Scheme in India." *European Journal of Political Economy* 41:14–30.

Imbert, Clement and John Papp. 2015. "Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee." *American Economic Journal: Applied Economics* 7(2):233–63.

Isaksson, Ann-Sofie, Andreas Kotsadam and Måns Nerman. 2014. "The Gender Gap in African Political Participation: Testing Theories of Individual and Contextual Determinants." *Journal of Development Studies* 50(2):302–318.

Jenkins, Rob and James Manor. 2017. *Politics and the Right to Work: India's National Rural Employment Guarantee Act*. London: Hurst and Company.

Kandpal, Eeshani and Kathy Baylis. 2019. "The social lives of married women: Peer effects in female autonomy and investments in children." *Journal of Development Economics* 140:26–43.

Khera, Reetika and Nandini Nayak. 2009. "Women Workers and perceptions of the National rural employment Guarantee act." *Economic and Political Weekly* 44(43):49–57.

Kjelsrud, Anders, Kalle Moene and Lore Vandewalle. 2020. "The Political Competition over Life and Death – Evidence from Infant Mortality in India." Graduate Institute Geneva Working Paper.

Klasen, Stephan and Janneke Pieters. 2015. "What Explains the Stagnation of Female Labor Force Participation in Urban India?" *The World Bank Economic Review* 29(3):449–478.

Knutsen, Tora and Andreas Kotsadam. 2020. "The political economy of aid allocation: Aid and incumbency at the local level in Sub Saharan Africa." *World Development* 127:104729.

Laakso, Markku and Rein Taagepera. 1979. ""Effective" Number of Parties. A Measure with Application to West Europe." *Comparative Political Studies* 12(1):3–27.

Lijphart, Arend. 1997. "Unequal Participation: Democracy's Unresolved Dilemma Presidential Address, American Political Science Association, 1996." *American Political Science Review* 91(1):1–14.

Margalit, Yotam. 2019. "Political Responses to Economic Shocks." *Annual Review of Political Science* 22:277–295.

Nickell, Stephen. 1981. "Biases in dynamic models with fixed effects." *Econometrica* 49(6):1417–1426.

Olausson, Maxine. 2017. "Women's perception of participation in NREGA, empowerment as a process of change.: A comparative Minor Field Study between two villages in Andhra Pradesh, India." Bachelor Thesis, Uppsala University.

Pop-Eleches, Cristian and Grigore Pop-Eleches. 2012. "Targeted Government Spending and Political Preferences." *Quarterly Journal of Political Science* 7(3):285–320.

Prillaman, Soledad Artiz. 2021. "Strength in numbers: How women's groups close India's political gender gap." *American Journal of Political Science* Forthcoming.

Ravi, Shamika and Monika Engler. 2015. "Workfare as an Effective Way to Fight Poverty: The Case of India's NREGS." *World Development* 67:57–71.

Robinson, Amanda Lea and Jessica Gottlieb. 2019. "How to Close the Gender Gap in Political Participation: Lessons from Matrilineal Societies in Africa." *British Journal of Political Science* 51(1):1–25.

Schlozman, K., N. Burns and S. Verba. 1999. ""What Happened at Work Today?": A Multistage Model of Gender, Employment, and Political Participation." *The Journal of Politics* 61(1):29–53.

Susewind, Raphael. 2016. "Data on religion and politics in India." Published under an ODbL 1.0 license. Available from https://github.com/raphael-susewind/india-religion-politics.

Zimmermann, Laura. 2020. "The Dynamic Electoral Returns of a Large Anti-Poverty Program." *Review of Economics and Statistics* Forthcoming.

Appendix 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:

$$Turnout\ Females_{2014} = \frac{turnout_{2014} - male\_votes_{2014}}{((electors_{2012} + electors_{2017})/2) * women\_percent_{2014}}$$

$$Turnout\ Females_{2017} = \frac{turnout_{2017} - male\_votes_{2017}}{electors_{2017} * women\_percent_{2014}}$$

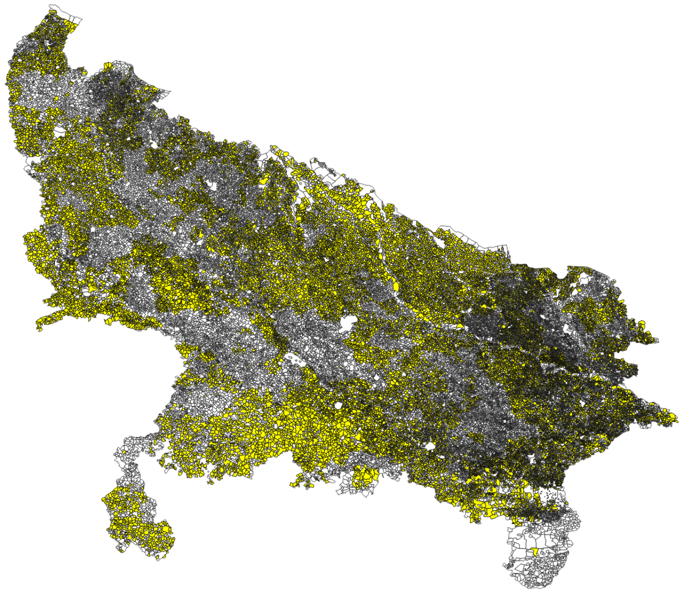
Male turnout is measured in a similar fashion. In addition to these measures, we construct the following alternative turnout rate for 2014, using the number of eligible voters in 2014 directly, instead of averaging over 2012 and 2017:

$$Turnout\ Females_{2014,alt} = \frac{turnout_{2014} - male\_votes_{2014}}{electors_{2014} * women\_percent_{2014}}$$

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 A2 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.[5] In total, we are able to match the Census and the NREGS dataset for about 76 percent of all Gram Panchayats in Uttar Pradesh.[6] Figure A3 maps the Census villages in the NREGS sample.

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

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

Figure A2: Map of NREGS sample

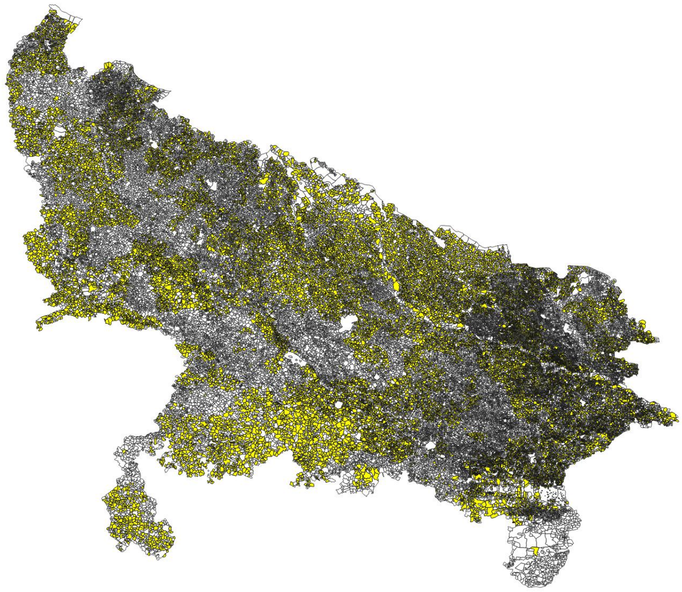
Note: The yellow areas display the Census villages included in the NREGS sample.

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 A4 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 A3. 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.

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

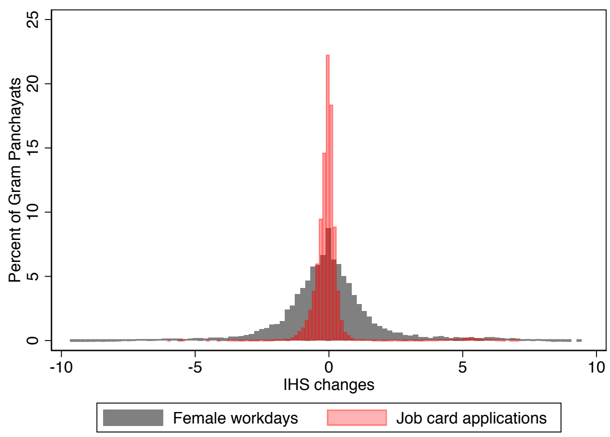
	Sample (1)	Missing observations (2)
Panel A: Population (Gram Panchayats) (*Different samples vs. Census*)		
NREGS sample	2743	2462
	N=44,085	*N=13,965*
Polling booth sample	3032	2368
	N=26,890	*N=31,160*
Estimation sample	2998	2491
	N=21,116	*N=36,934*
Panel B: NREGS workdays (*Estimation sample vs. 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*

Appendix 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 A5 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 A4). 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 A4).

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

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.

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

$$\Delta\text{IHS}(Female\ workdays_{jkl}) = \gamma V_{ijkl} + \theta_{kl} + e_{ijkl}, \tag{A2}$$

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 A5 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.

Appendix 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.

Appendix 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 A6 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 A7 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)
$\Delta\text{Log}(\textit{Female workdays} + 1)$	0.09591***		
	(0.02750)		
$\Delta\textit{Female workdays}$		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 A8 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 A9, 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 A10.

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 (1)	Min match score> .75 (2)	Full match (3)	Alternative turnout rate (4)	Collapsed to GPs (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.

Appendix 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 A11).

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 A11 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 A12. 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 (1)	Current MLAs (2)	Current MPs (3)	SP (4)	BJP (5)	INC (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.

Appendix 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).[7]

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 A13. 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 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.

In the rest of Table A13 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

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

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.

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 A14, A15 and A16 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 A14 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 A15 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 A16 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.