Supplemental Information for: "A Moveable Benefit? Spillover Effects of Quotas on Women's Numerical Representation"

June 5, 2022

Contents

1 Parallel trends **2**

2 DID weights **5**

3 Additional results **6**

3.1 Post-treatment effects 6

3.2 Examining deposit loss 6

3.3 Alternative specification: 33% reservation 8

3.4 Alternative specification: Inclusion of lagged dependent variable 10

3.5 Dropping Karnataka and Andhra Pradesh 10

4 pVARs, Granger-causality tests and IRFs **10**

4.1 Full Granger-causality results 14

4.2 Additional IRFs 14

1 Parallel trends

As discussed in the main manuscript, one assumption underlying DID is that of parallel trends. To test this we create dichotomous variables equal to one for all elections before and after the 50% local-level reservation, and zero otherwise (Cerulli and Ventura 2019; Cunningham 2021). In other words, $D_{i,t-1}, D_{i,t-2}, D_{i,t-3}, \cdots$ are dichotomous variables equal to one in state i the first, second, and third elections *before* the 50% reservation was enacted, respectively, while $D_{i,t}, D_{i,t+1}$ is equal to one in state i the first and second observed elections after a state enacted a 50% quota, respectively. There were at most nine elections held before a quota reservation in our dataset, and up to two held after. We then include all of these leads and lags (keeping $D_{i,t}$ as the omitted category) in a regression model with both election and state fixed effects (i.e., analogous to our first DID outlined in the main manuscript in Equation 1). These of course are heavily-parameterized models, but they help to examine the pre-treatment coefficients across election periods to test whether the assumptions of parallel trends are met.

Our parallel trend test results are shown in Figures S1 through S5 for each of our five outcome variables. Keeping with popular convention (c.f., Cerulli and Ventura 2019), we plot these coefficient horizontally across time rather than showing regression tables since it is a bit easier to see visual trends using this technique, and the vertical dashed line indicates the first election after the 50% reservation (recall that this D_{it} coefficient is the omitted/baseline category). Across all dependent variables—Figures S1 through S5—there are very few (5 out of 45) statistically significant coefficients in the pre-treatment period, and nothing resembling a consistent pattern across pre-treatment election coefficients that suggests that the parallel trend assumption may be violated.

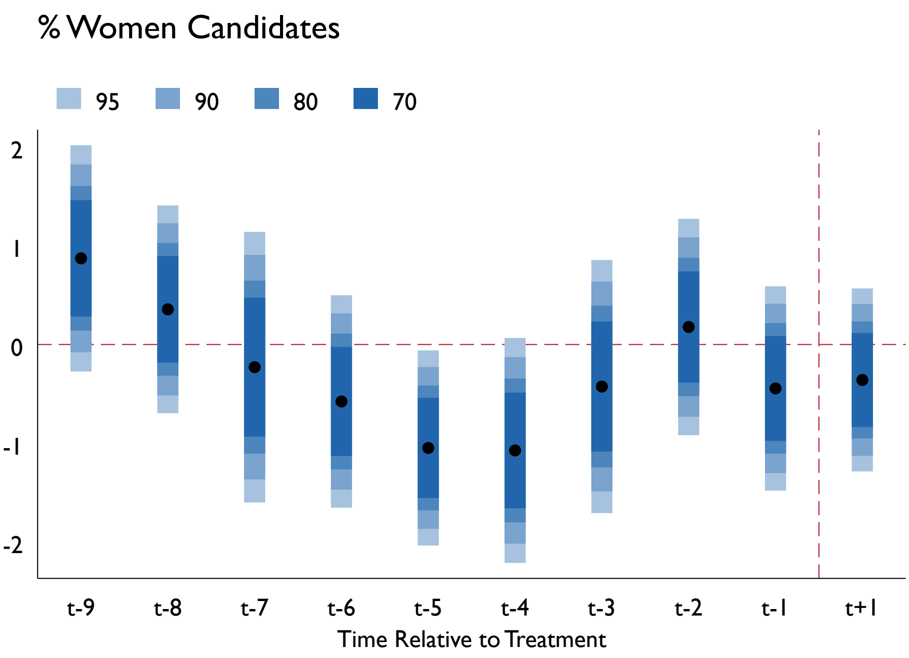

Figure S1: Parallel trends: Percentage of women candidates

Note: Plot shows coefficients with 70 through 95 percent confidence intervals shown. Clustered standard errors by state used.

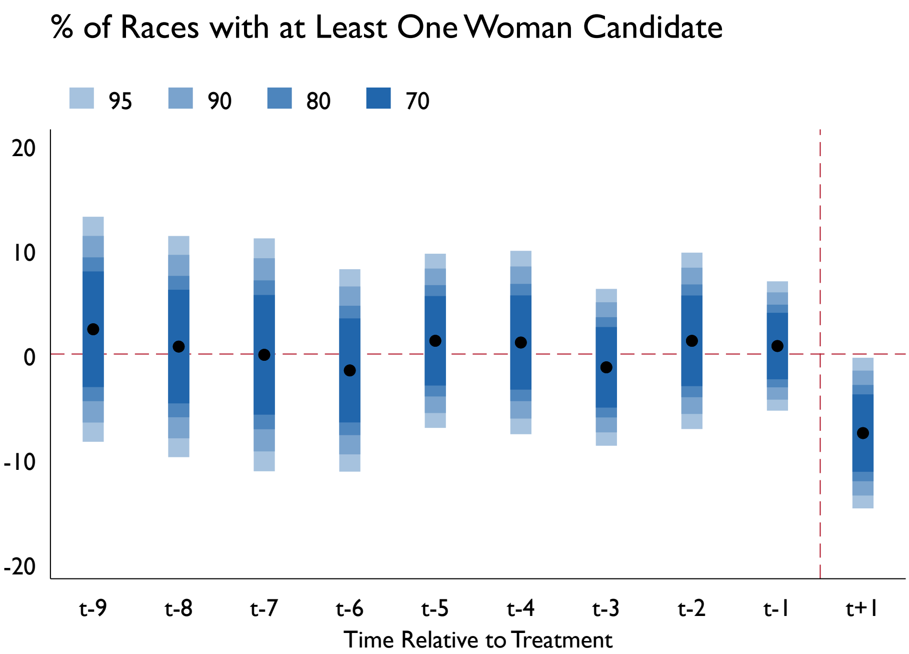

Figure S2: Parallel trends: Percentage of races with at least one woman candidate

Note: Plot shows coefficients with 70 through 95 percent confidence intervals shown. Clustered standard errors by state used.

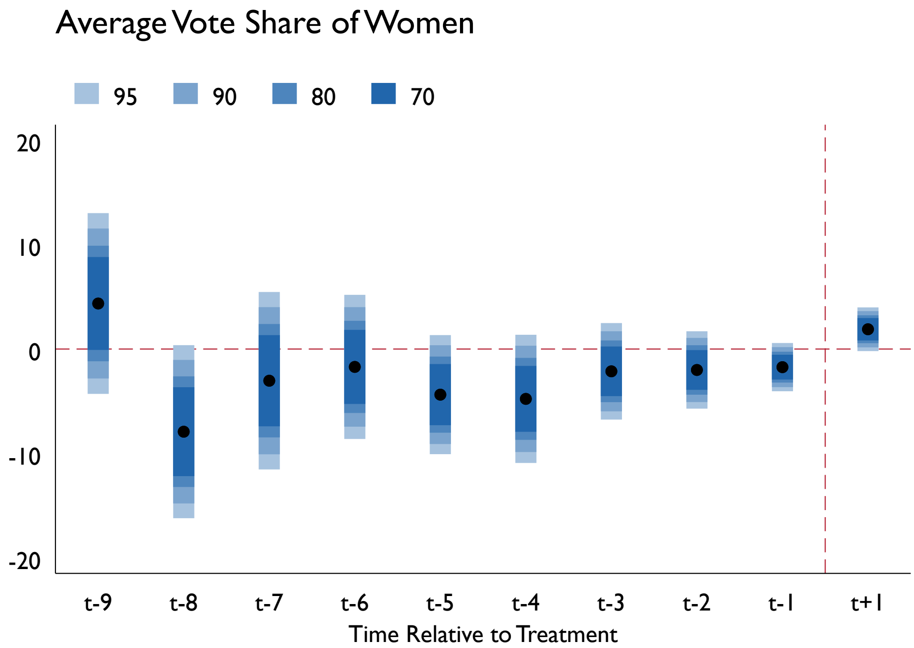

Figure S3: Parallel trends: Average vote share of women

Note: Plot shows coefficients with 70 through 95 percent confidence intervals shown. Clustered standard errors by state used.

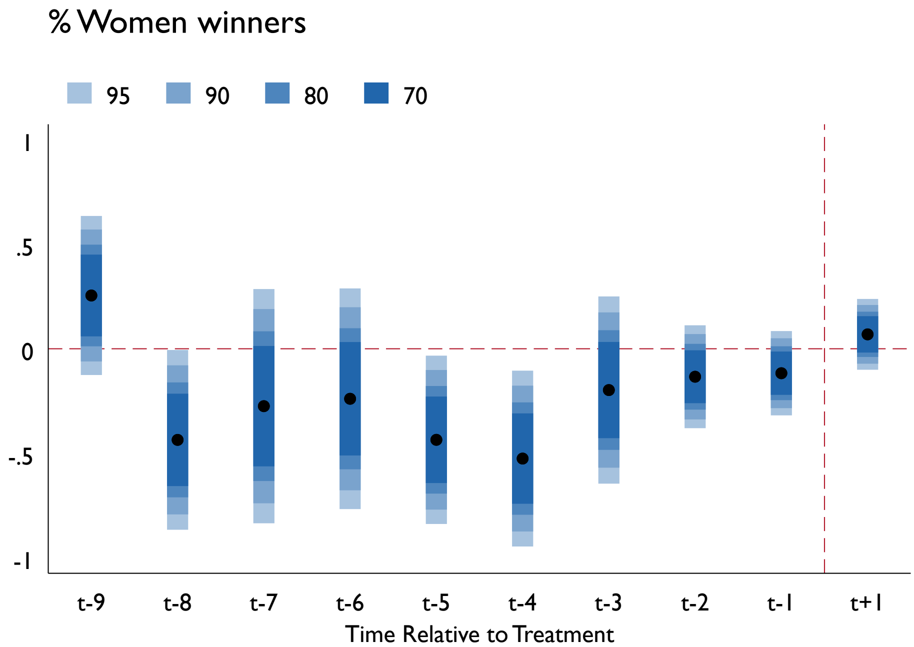

Figure S4: Parallel trends: Percentage of women winners

Note: Plot shows coefficients with 70 through 95 percent confidence intervals shown. Clustered standard errors by state used.

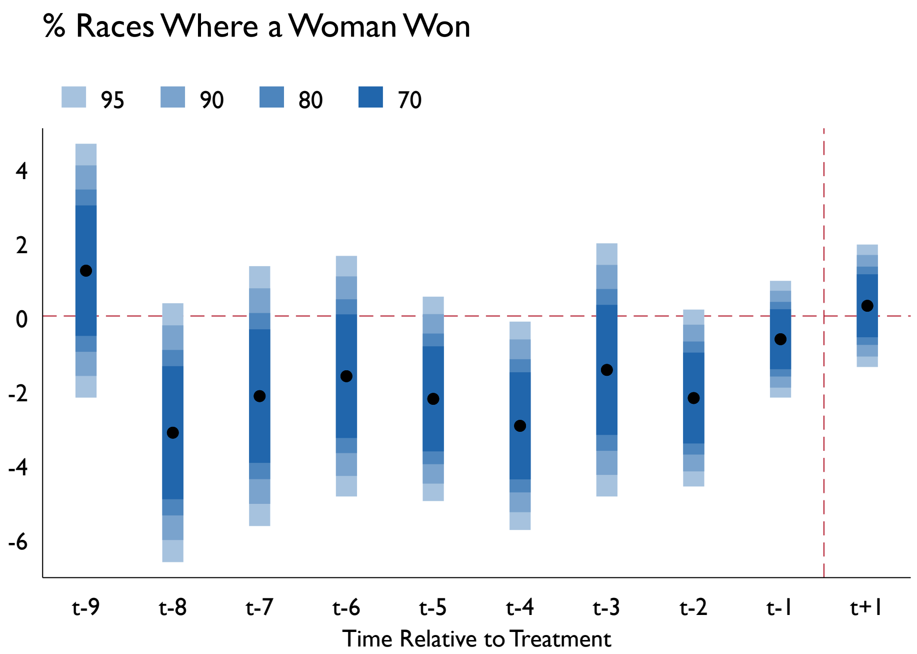

Figure S5: Parallel trends: Percent races where a woman won

Note: Plot shows coefficients with 70 through 95 percent confidence intervals shown. Clustered standard errors by state used.

2 DID weights

As discussed in De Chaisemartin and d'Haultfoeuille (2020) (see also Imai and Kim (2021)), the overall DID estimate that we present comes from multiple weighted average treatment effects for each unit that are summed together. In doing so, we run the risk of creating negative weights if heterogeneity exists in the treatments, which—at its extreme—may result in a negative average treatment effect even though all individual treatment effects are positive (intuitively, we are multiplying a positive ATE for a unit by a negative weight, producing a negative ATE for that unit). As shown in Table S1 we find that across all of our outcomes we have no negative weights, which suggests that the biased ATE/DID estimate that may occur in the presence of negative weights does not appear to be affecting our results.

Table S1: No negative weights in our DID models

Dependent variable	Fraction of negative weights:	
	Assumption 1	Assumption 2
% Women candidates	0	0
% races with at least one woman candidate	0	0
Vote share	0	0
% Women winners	0	0
% Races with women winners	0	0

Note: Weight calculation done using the approach in De Chaisemartin and d'Haultfoeuille (2020). Assumption 1: common trend; DID coefficient comes from a weighted sum of 25 state-level ATTs. Assumption 2: under common trends, treatment monotonicity and no time-varying treatment effect; DID coefficient comes from a weighted sum of 17 LATEs.

3 Additional results

3.1 Post-treatment effects

As discussed above, there are at most two state-level elections held after a state enacted a local-level 50% quota reservation. While this is not ideal for analyzing long-run dynamic, post-treatment effects that might grow smaller or larger over time, it is still useful to see if the effects size appears to grow larger or smaller over our (albeit small) timeframe. Including D_{it} and $D_{i,t+1}$ in our DID specifications from the main manuscript, we show the updated results for both supply- (Table S2) and demand-side (Table S3) factors. If anything, it appears that the effects are of similar sign but larger in magnitude as time goes.

3.2 Examining deposit loss

In Table S4 we show the results for an additional variable, deposit loss. As a result of the 50% local-level reservation, there is clear evidence that the percent of women candidates losing their deposit goes down (by between about 6 and 9 percentage points), suggesting that women who are competing are far more competitive (since the command a high enough percentage of the total vote to avoid losing their

Table S2: Examining post-treatment effects: Supply-side factors

	Dependent variable:			
	% Women candidates		% Races with at least one woman candidate	
	(1)	(2)	(3)	(4)
D_{it}	0.467	0.473	-0.779	-1.062
	(0.41)	(0.50)	(2.95)	(3.25)
$D_{i,t+1}$	0.202	0.209	-8.440*	-8.772*
	(0.67)	(0.79)	(4.63)	(4.73)
State FE	Y	Y	Y	Y
Election FE	Y	Y	Y	Y
Treated state*Election trend		Y		Y

Note: 194 observations. Coefficients shown with standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table S3: Examining post-treatment effects: Demand-side factors

	Dependent variable:					
	Vote share		% Women winners		% Races with women winners	
	(5)	(6)	(7)	(8)	(9)	(10)
D_{it}	2.277*	1.831	0.198*	0.149	1.444	1.193
	(1.32)	(1.38)	(0.10)	(0.12)	(0.90)	(1.11)
$D_{i,t+1}$	4.093**	3.571*	0.276***	0.220	1.739	1.445
	(1.68)	(1.89)	(0.09)	(0.15)	(1.10)	(1.32)
State FE	Y	Y	Y	Y	Y	Y
Election FE	Y	Y	Y	Y	Y	Y
Treated state*Election trend		Y		Y		Y

Note: 194 observations. Coefficients shown with standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

deposit).

Table S4: Deposit loss

	Dependent variable:	
	Deposit loss	
	(11)	(12)
50% reservation	-5.840*	-9.213***
	(3.055)	(2.933)
State FE	Y	Y
Election FE	Y	Y
Treated state*Election trend		Y
Observations	194	194
R^2	0.981	0.983
Adjusted R^2	0.977	0.977

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

3.3 Alternative specification: 33% reservation

In Table S5 we show our results with the inclusion of a dummy variable equal to one for all state elections that took place after the 1992 constitutional amendment for the 33 percent reservation. We do the same for vote share and deposit loss in Table S6, and for the percentage of women winners and the percentage of races with women winners in Table S7. Our results are robust to the inclusion of this variable.

Table S5: Adding 33% quota: Supply-side variables

	Dependent variable:			
	% Women candidates		% Races with at least one woman candidate	
	(13)	(14)	(15)	(16)
33% reservation	1.192***	1.149***	-0.509	-0.765
	(0.402)	(0.435)	(3.182)	(3.228)
50% reservation	0.515	1.091**	-2.588	-0.630
	(0.454)	(0.533)	(3.383)	(4.008)
State FE	Y	Y	Y	Y
Election FE	Y	Y	Y	Y
Treated state x Election trend		Y		Y
Observations	194	194	194	194
R^2	0.970	0.974	0.967	0.969
Adjusted R^2	0.963	0.965	0.959	0.959

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table S6: Impact of women's reservation on demand side variables

	Dependent variable:			
	Vote share		Deposit loss	
	(17)	(18)	(19)	(20)
33% reservation	0.953	1.559	-2.532	-3.586
	(1.375)	(1.191)	(4.119)	(3.377)
50% reservation	2.782*	4.104***	-6.071*	-9.475***
	(1.515)	(1.430)	(3.130)	(2.956)
State FE	Y	Y	Y	Y
Election FE	Y	Y	Y	Y
Treated state x Election trend		Y		Y
Observations	194	194	194	194
R^2	0.933	0.939	0.982	0.983
Adjusted R^2	0.917	0.921	0.977	0.977

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table S7: Impact of women's reservation on demand side variables

	Dependent variable:			
	% Women winners		% Races with women winners	
	(21)	(22)	(23)	(24)
33% reservation	0.125	0.119	0.365	0.539
	(0.087)	(0.099)	(0.647)	(0.763)
50% reservation	0.227**	0.289**	1.546	2.287*
	(0.100)	(0.132)	(0.979)	(1.233)
State FE	Y	Y	Y	Y
Election FE	Y	Y	Y	Y
Treated state*Election trend		Y		Y
Observations	194	194	194	194
R^2	0.835	0.842	0.890	0.898
Adjusted R^2	0.796	0.792	0.864	0.866

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

3.4 Alternative specification: Inclusion of lagged dependent variable

In Table S8, we also include a lagged dependent variable in each of our regression models. Note that the number of observations drop considerably with the inclusion of these lags.

Table S8: Outcomes using alternate specifications with lagged dependent variables

	% Women candidates	Vote share	Deposit loss	% Women winners	% Races with at least one woman candidate	% Races with women winners
	(25)	(26)	(27)	(28)	(29)	(30)
33% reservation	1.224*	3.142	-5.475	0.351**	-3.317	1.666*
	(0.707)	(1.913)	(4.644)	(0.167)	(5.244)	(0.915)
50% reservation	1.019*	3.896**	-8.493***	0.224*	-1.491	0.930
	(0.583)	(1.830)	(3.248)	(0.120)	(4.155)	(1.064)
Lagged DV	0.166*	0.087	0.068	0.313***	0.109	0.328***
	(0.092)	(0.136)	(0.101)	(0.107)	(0.113)	(0.061)
State FE	Y	Y	Y	Y	Y	Y
Election FE	Y	Y	Y	Y	Y	Y
Observations	116	116	116	116	116	116
R^2	0.975	0.935	0.986	0.882	0.972	0.931
Adjusted R^2	0.967	0.915	0.981	0.844	0.964	0.909

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

3.5 Dropping Karnataka and Andhra Pradesh

In Table S9 we show the results of supply-side variables when we drop two states, Karnataka and Andhra Pradesh, from the regression. The sample size drops from 194 to 175 with these two states excluded. Our findings are robust to these changes, as they are for the demand-side variables when we drop the same two states, as done in Table S10.

4 pVARs, Granger-causality tests and IRFs

In the main manuscript we estimated a panel vector autoregressive (pVAR) model in order to parse out whether supply or demand factors may cause one another. Using the strategy outlined in Abrigo and Love (2016), we searched across plausible models using one lag of each variable with GMM-style instruments, cross-sectional means removed, and robust standard errors clustered by state. Key to pVARs are establishing

Table S9: Supply side variables - Excluding Karnataka and Andhra Pradesh

	Dependent variable:			
	Candidates		% races with at least one woman candidate	
	(31)	(32)	(33)	(34)
33% reservation	1.139***	1.064**	-0.567	-0.569
	(0.411)	(0.456)	(3.581)	(3.741)
50% reservation	0.491	0.901	-3.230	0.872
	(0.479)	(0.718)	(4.093)	(5.269)
State FE	Y	Y	Y	Y
Election FE	Y	Y	Y	Y
Treated state*Election trend		Y		Y
Observations	175	175	175	175
R^2	0.971	0.974	0.965	0.968
Adjusted R^2	0.964	0.966	0.957	0.958

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table S10: Demand side variables - Excluding Karnataka and Andhra Pradesh

	Dependent variable:							
	Vote share		Deposit loss		Winners Winners		% races with women winners	
	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)
33% reservation	0.600	1.000	-1.666	-2.185	0.108	0.076	0.352	0.329
	(1.592)	(1.376)	(4.738)	(3.809)	(0.087)	(0.091)	(0.596)	(0.741)
50% reservation	3.484***	5.059***	-7.282**	-10.641***	0.266**	0.278	1.896*	2.559*
	(1.649)	(1.886)	(3.396)	(4.055)	(0.112)	(0.203)	(1.091)	(1.508)
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Election FE	Y	Y	Y	Y	Y	Y	Y	Y
Treated state*Election trend		Y		Y		Y		Y
Observations	175	175	175	175	175	175	175	175
R^2	0.934	0.941	0.981	0.982	0.838	0.844	0.895	0.902
Adjusted R^2	0.918	0.922	0.976	0.976	0.895	0.902	0.868	0.870

Note: Standard errors clustered by state are given in parentheses. *p<0.1; **p<0.05; ***p<0.01.

whether the eigenvalues from the equation lie inside the unit circle, which means that the pVAR can be rewritten as an infinite-order vector moving average representation. This implies that the model is stable, which is necessary for creating impulse response functions and causality testing. As shown in Figure S6, all eigenvalues lie inside the unit circle, which means the pVAR satisfies the stability condition.

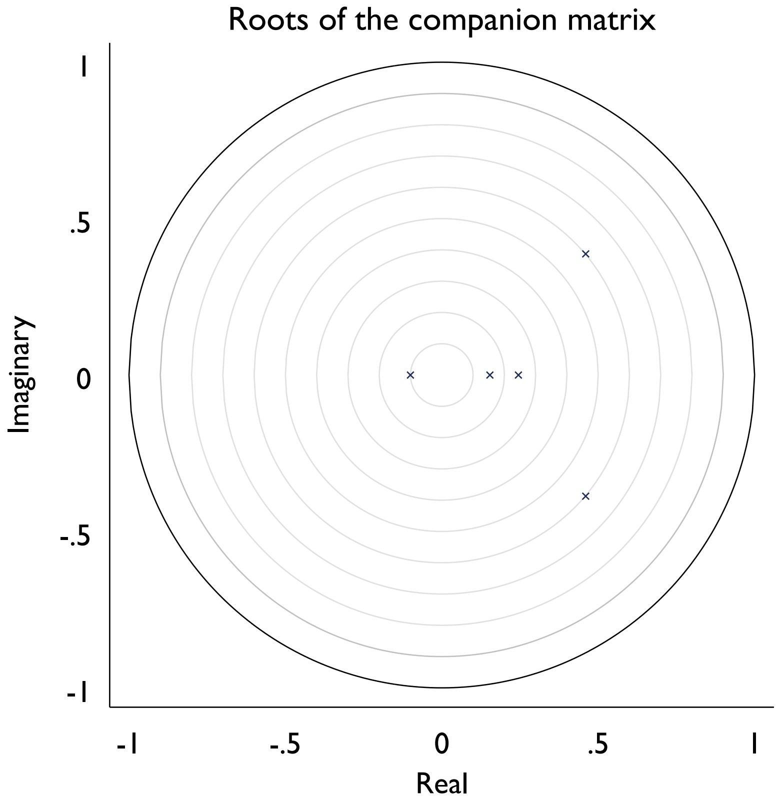

Figure S6: The pVAR is Stable

Since the pVAR is estimated using a GMM framework, we also need to select the number of instruments. We found that using instruments at both $t-1$ and $t-2$ of all endogenous variables (i.e., the five dependent variables analyzed throughout the main manuscript) as well as the 50% reservation dichotomous treatment variable instrumented at t and $t-1$ ensured a good model fit according to AIC and BIC, while also still passing Hansen's J-test of overidentifying restrictions.[1] The full set of results are shown in Table S11.

[1]The statistic was 5.34, which failed to reject the null hypothesis. This suggests that the instruments are valid.

Table S11: Panel vector autoregression results

	% Women candidates	% Races with at least one woman candidate	Vote share of women candidates	% Women winners	% Races with women winners
% Women candidates$_{t-1}$	0.167 (0.255)	0.132 (1.380)	-0.047 (0.799)	0.010 (0.068)	0.060 (0.464)
% Races with at least one woman candidate$_{t-1}$	-0.016 (0.054)	0.206 (0.275)	-0.261 (0.134)	0.003 (0.011)	-0.011 (0.074)
Vote share of woman candidates$_{t-1}$	0.011 (0.038)	0.092 (0.206)	0.094 (0.151)	0.005 (0.015)	0.089 (0.098)
% Women winners$_{t-1}$	-2.642** (0.995)	-12.679* (5.820)	-6.832 (3.791)	-0.199 (0.184)	-4.373** (1.516)
% Races with woman winners$_{t-1}$	0.459* (0.199)	2.321* (1.001)	1.203 (0.691)	0.087* (0.036)	0.951*** (0.278)
50% Reservation$_t$	-0.131 (1.788)	-5.002 (8.827)	-1.985 (4.280)	0.513 (0.364)	0.510 (2.643)
50% Reservation$_{t-1}$	-0.165 (0.718)	-7.845 (5.382)	0.174 (2.529)	0.134 (0.151)	-0.292 (1.202)

Note: Panel vector autoregressive coefficients with clustered standard errors by state in parentheses. Two-tailed tests. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Hansen's J-test of overidentifying restrictions: 5.34 (p= 1.00). GMM-style instruments used (lags at $t-1$ and $t-2$ of all endogeneous variables, and the 50% reservation variable at t and $t-1$. Forward orthogonal deviation used to remove state fixed effects, and cross-sectional means removed from all variables to purge cross-sectional dependence time-varying effects common to all states.

4.1 Full Granger-causality results

In the main manuscript we showed a simplified version of Granger-causality tests based on the results from S11. In Table S12 we present the actual χ^2 values (and associated p-values) for each of the Wald tests performed.

Table S12: Granger-Causality Tests With χ^2 Values

	Supply-Side		Demand-Side		
$b \Downarrow$ "Granger-Causes" $a \Rightarrow$	% of Women Candidates	% of Races with at Least 1 Woman Candidate	Vote Share of Women Candidates	% Women Winners	% of Races with Women Winners
% Women Candidates	*n/a*	0.01	0.003	0.02	0.02
% of Races with at Least 1 Woman Candidate	0.09	*n/a*	3.77^{*}	0.09	0.02
Vote Share of Women Candidates	0.09	0.20	*n/a*	0.13	0.81
% Women Winners	7.04^{**}	4.75^{**}	3.25^{*}	*n/a*	8.32^{**}
% of Races with Women Winners	5.34^{**}	5.37^{**}	3.03^{*}	6.00^{**}	*n/a*

Note: Individual exogeneity tests show whether row b Granger-causes column a, using Wald tests from the estimated pVAR. H_0 : the excluded b does not Granger-cause equation variable a. χ^2 values shown, with 1 degree of freedom. $**$: $p < 0.05$; $*$: $p < 0.10$.

4.2 Additional IRFs

In the main manuscript we showed two of the five sets of impulse response functions. In Figures S7, S8 and S9 we show the effect of impulses to the percentage of women candidates, the percentage of races with at least one woman candidate, and women's vote share, respectively.[2] As is clear from these results, none of the corresponding responses achieve statistical significance at conventional levels, although

[2]Note that the procedure used for bootstrapping confidence intervals cannot be used with clustered standard errors (which we used in Table S11 in order to remain consistent with the rest of our estimation strategy throughout the rest of the paper).

vote share does decline at the 90% level of significance in response to a positive increase in the percentage of races with at least one woman (shown in Figure S8).

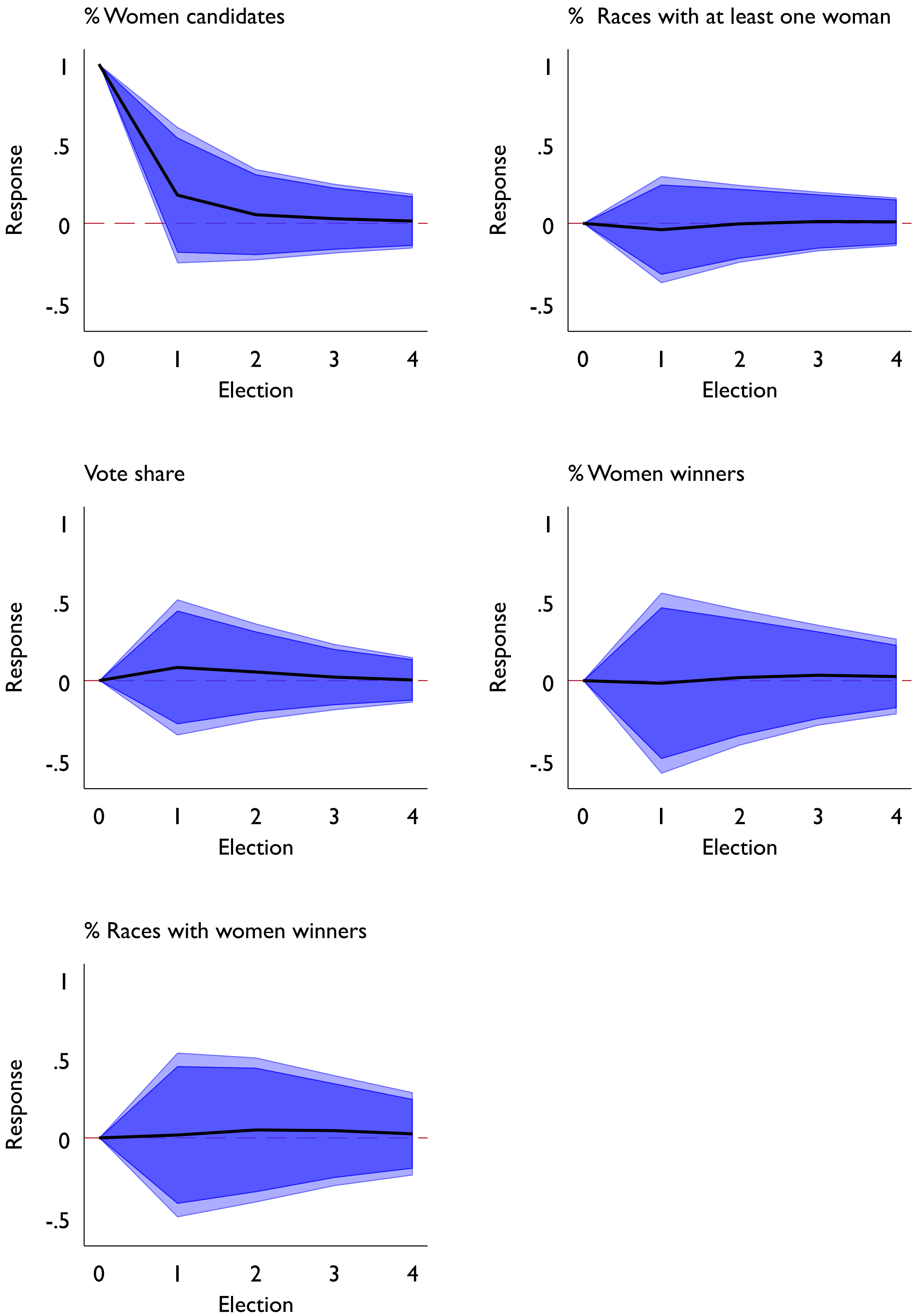

Figure S7: Effect of a +1 standard deviation impulse of % of women candidates on all supply- and demand-side outcomes

Note: Estimated response along with 90% (dark blue) and 95% (light blue) bootstrapped confidence intervals shown. All variables standardized.

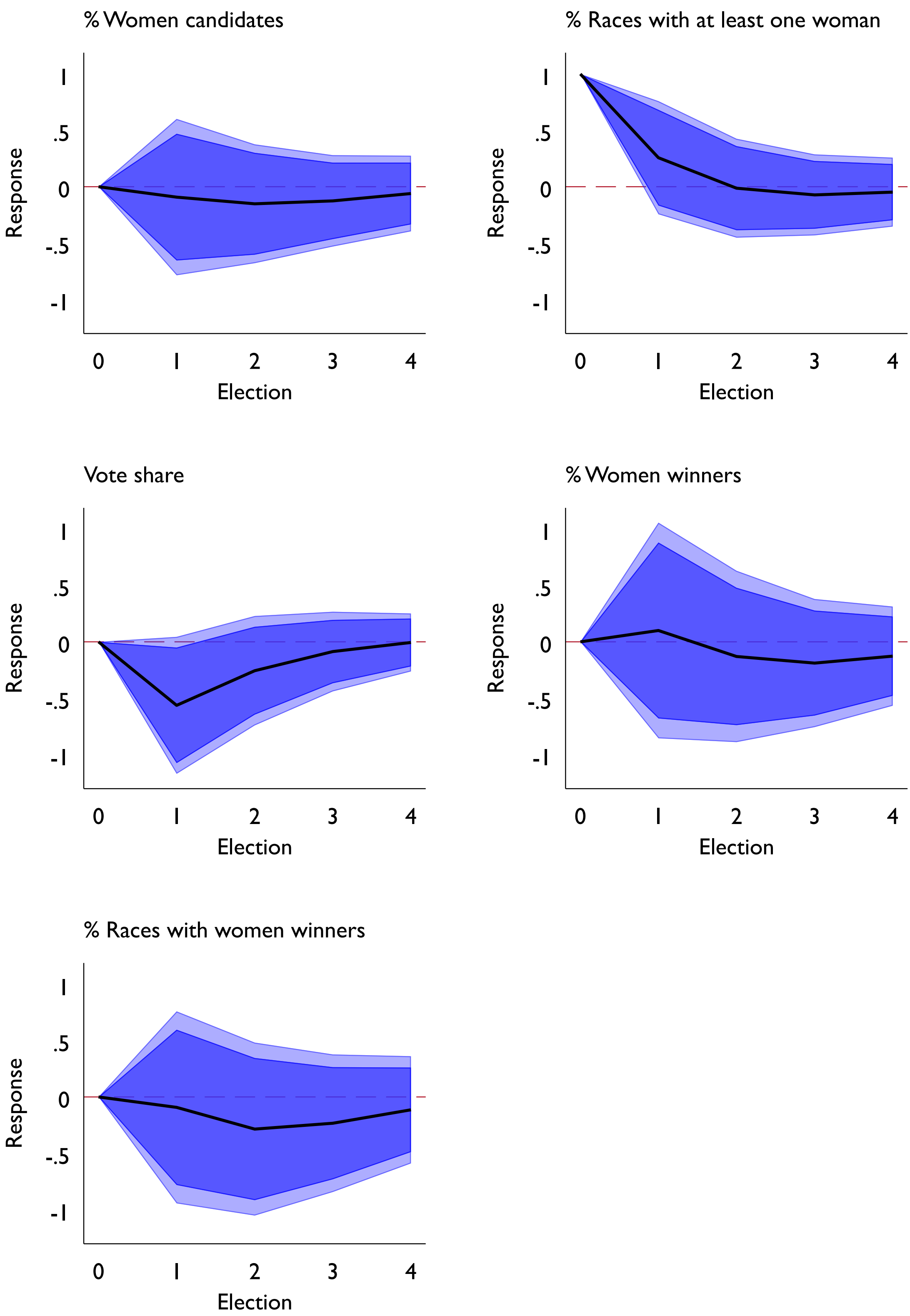

Figure S8: Effect of a +1 standard deviation impulse of % races with at least one woman candidate on all supply- and demand-side outcomes

Note: Estimated response along with 90% (dark blue) and 95% (light blue) bootstrapped confidence intervals shown. All variables standardized.

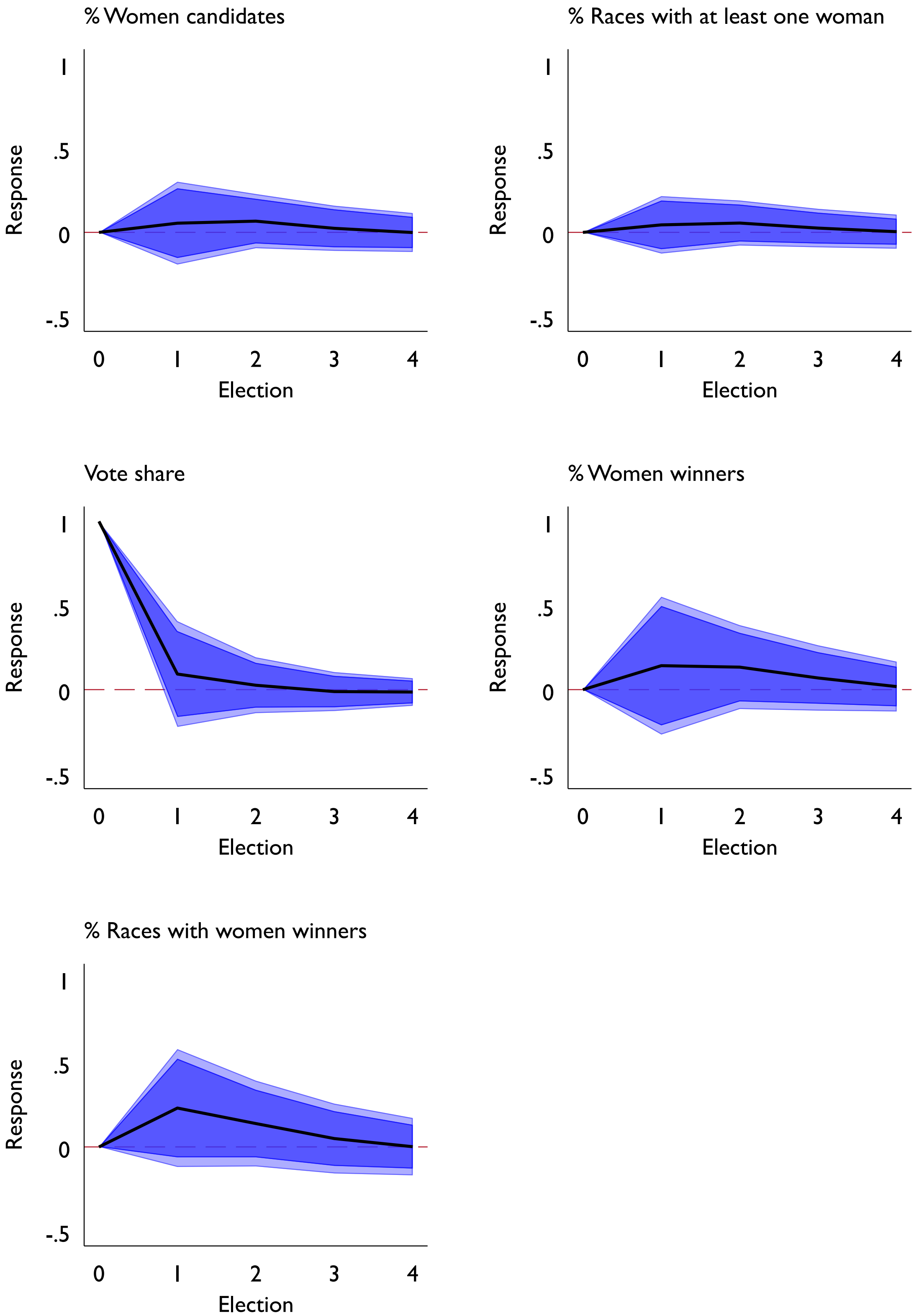

Figure S9: Effect of a +1 standard deviation impulse of women's vote share on all supply- and demand-side outcomes

Note: Estimated response along with 90% (dark blue) and 95% (light blue) bootstrapped confidence intervals shown. All variables standardized.

References

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