Electoral Backlash or Positive Reinforcement? Wind Power and Congressional Elections in the United States

Supporting Information

Johannes Urpelainen
Johns Hopkins SAIS

Alice Tianbo Zhang
Washington and Lee University

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A1 Formal Models of Retrospective Voting

We introduce two models of retrospective voting. In one, a naive voter simply supports the incumbent if the outcome is good enough. In another, a sophisticated voter uses the outcome to make a rational decision about the merits of Democratic and Republican candidates.

In both models, pre-existing wind energy capacity $\theta \in [0, \infty)$ is considered exogenous. The voter's utility $u(\theta)$ is assumed to be strictly monotonic. For some voters, u is strictly increasing in θ; for others, u is strictly decreasing in θ.

A1.1 Naive Retrospection

In this model, the voter supports the current incumbent if and only if $u(\theta) \geq t$, where t is some arbitrary and exogenously given threshold for a good outcome. Given this framework, the voter's support for the incumbent depends on pre-existing wind energy capacity. If u is strictly increasing in θ, then the incumbent gains the voter's support as long as θ exceeds some minimal threshold induced by t. If u is strictly decreasing in θ, then θ must fall below t.

The empirically observable implication of naive retrospection is that wind energy capacity has a monotonous effect on support for the incumbent, regardless of the incumbent's partisanship. Whether the effect is positive or negative depends on the relative number of voters who benefit (positive reinforcement) or lose (electoral backlash) from wind energy deployment.

A1.2 Sophisticated Retrospection

In this model, the voter's support does not depend on incumbency. Let $t(\theta)$ be a strictly decreasing function below $\underline{\theta}$ and strictly increasing above $\underline{\theta}$. The voter observes θ and then supports a Democratic candidate if and only if:

- $\theta \geq \underline{\theta}, u(\theta) \geq t(\theta)$; or
- $\theta < \underline{\theta}, u(\theta) < t(\theta)$.

In this model, the retrospective voter observes pre-existing wind capacity and the payoff from this capacity. If pre-existing capacity is low, then the voter only supports a Democratic candidate when the payoff is low; if pre-existing capacity is high, then the voter only supports a Democratic candidate when the payoff is high. Intuitively, the voter supports Democratic candidates, who are pro-wind, whenever wind energy capacity appears to be associated with a good outcome. In this sense, the voter is using retrospection to learn about the qualities of wind energy.

The empirically observable implication is that positive reinforcement in favor of Democratic candidates is generated when many voters see outcomes improve with growing pre-existing wind capacity; electoral backlash against Democratic candidates is generated when many voters see outcomes worsen with growing pre-existing wind capacity.

A2 Data Description

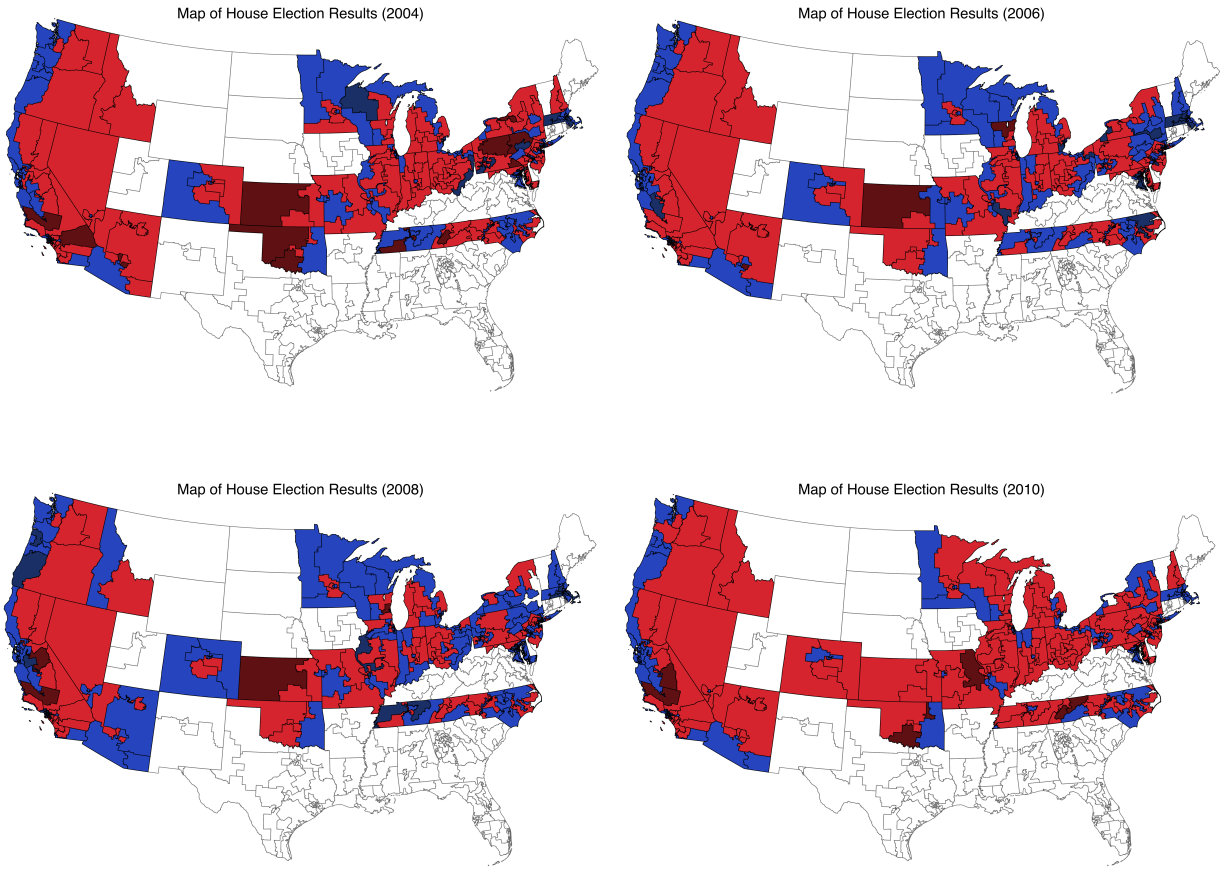
- Table A1 presents summary statistics of the response (roll call vote and election outcomes), explanatory (wind turbine installation) and instrumental (zonal wind potential) variables in the state-district-year panel. We exclude states that do not have any windmills, those that have only one district, and those that do not have districts with and without wind farms during the sample period of 2003-2012. We also exclude Texas due to boundary changes (gerrymandering). In subsequent analysis of election outcomes, we collapse the data into state-district-election periods for biennial congressional election between 2004-2012.
- Table A2 presents summary statistics of election variables in the state-district-election period panel.

Table A1: Summary Statistics of Variables in the State-District-Year Panel

	Mean	SD	Min	Max	Obs
Wind Turbine Installation					
Cumulative number of wind turbines	71.40	408.17	0	5040	2870
Cumulative capacity of wind turbines (MW)	45.57	209.71	0	2936	2870
Number of wind turbines	6.33	35.62	0	680	2870
Capacity of wind turbines (MW)	11.18	65.45	0	1321	2864
Zonal Wind Potential					
mean of zonal wind potential	1.70	0.52	1	4	2870
std of zonal wind potential	0.52	0.32	0	2	2870
min of zonal wind potential	1.13	0.34	1	2	2870
median of zonal wind potential	1.57	0.59	1	4	2870
max of zonal wind potential	3.56	1.75	1	7	2870
Roll Call Vote Outcome					
Pro-environment vote share	56.38	40.54	0	100	2868
Anti-environment vote share	40.15	40.31	0	100	2868
Election Outcome					
Incumbent vote share	69.82	13.83	39	100	2602
Democratic candidate vote share	55.39	23.05	0	100	2868
Republican candidate vote share	44.28	22.95	0	100	2867

- Figure A1 shows House election results for 2004, 2006, 2008 and 2010 in the 287 sample state-districts.
- Table A3 presents summary statistics of balance variables from the American Community Survey for districts with and without wind power, as compared to the full sample for the years 2005-2011. We consider a district to be 'with wind' if it has strictly greater than zero cumulative installed count or capacity of wind turbines.

Figure A1: Map of House Election Results 2004, 2006, 2008 and 2010



Notes: This map shows House election results for 2004, 2006, 2008 and 2010 in the 287 sample state-districts. We do not show the results for 2012 here because only 3 districts had special House elections in 2012.

Table A2: Summary Statistics of Variables in the State-District-Election Period Panel

	2004	2006	2008	2010
Total number of votes (thousand)	263.25	191.26	279.81	202.31
	(57.75)	(52.88)	(60.16)	(50.47)
Democratic candidates vote share (%)	54.07	59.64	61.03	51.54
	(23.99)	(22.07)	(21.70)	(19.23)
Republican candidates vote share (%)	45.93	40.36	38.97	48.46
	(23.99)	(22.07)	(21.70)	(19.23)
Third party candidates vote share (%)	2.01	0.00	0.00	0.00
	(3.51)	(0.00)	(0.00)	(0.00)
Incumbent candidates vote share (%)	71.50	69.78	70.72	64.72
	(12.67)	(14.93)	(14.24)	(12.96)
Number of Democrats in the House	201.01	232.00	257.00	194.12
	(0.24)	(0.00)	(0.00)	(8.42)
Number of Republicans in the House	233.00	203.31	178.53	242.00
	(0.00)	(3.06)	(3.60)	(0.00)
Number of Independents in the House	1.00	0.01	0.00	0.00
	(0.00)	(0.10)	(0.00)	(0.00)
Districts	287	287	285	285

Table A3: Summary Statistics of Baseline Characteristics by Treatment Status

	With Wind	Without Wind	Overall
Demographics			
Total population (thousand)	691.6	682.4	685.4
	(60.80)	(59.96)	(60.36)
White (%)	0.835	0.696	0.740
	(0.121)	(0.196)	(0.187)
Native, born outside of U.S. (%)	0.0104	0.0135	0.0125
	(0.00758)	(0.0120)	(0.0109)
Male (%)	0.494	0.491	0.492
	(0.00832)	(0.0121)	(0.0111)
Older than 65 (%)	0.135	0.124	0.127
	(0.0245)	(0.0237)	(0.0245)
Income & Poverty			
Median household income ($1000)	51.54	54.34	53.45
	(10.56)	(15.19)	(13.95)
Per capita income ($1000)	25.74	27.73	27.10
	(4.673)	(8.500)	(7.559)
Median gross rent ($)	768.6	904.9	861.7
	(194.8)	(251.7)	(243.5)
Income at or above poverty level (%)	0.852	0.843	0.846
	(0.0441)	(0.0645)	(0.0590)
Education			
Male with associate degrees and above	0.222	0.240	0.235
	(0.0554)	(0.0836)	(0.0763)
Female with associate degrees and above	0.235	0.251	0.246
	(0.0533)	(0.0771)	(0.0708)
Employment			
Employment in agriculture (%)	0.0247	0.0118	0.0159
	(0.0237)	(0.0228)	(0.0238)
Employment in manufacturing (%)	0.127	0.112	0.117
	(0.0516)	(0.0489)	(0.0502)
Mean hours worked	38.43	38.65	38.58
	(0.843)	(1.041)	(0.987)
Observations	637	1372	2009

A3 Balance Test

- In order for our research design to be valid, the instrument must satisfy the exclusion restriction. While there is no formal test for the exclusion restriction, we provide empirical evidence strongly suggesting that any other potential confounders of the outcome variables are balanced across districts with and without wind turbines. Wo do so by collecting and merging in annual census data from the American Community Survey (ACS) available for the years 2005-2011. Specifically, we run the following balance regressions similar to the first-stage regression, but with ACS census variables as the dependent variables:

$$\text{Balance Variables}_{ijt} = \alpha_i + \beta_{jt} + \gamma t \times \text{Wind Resource}_{ij} + \varepsilon_{ijt}. \quad (1)$$

- Tables A4, A5 and A6 present results from balance regressions using a comprehensive set of dependent variables across demographic, income, education and employment. The results suggest that our instrument, time trends in the mean wind potential for a congressional district, is unlikely to be correlated with potential confounders of electoral or congressional voting outcomes. The three exceptions are population (slightly faster growth in areas with good wind resource), the share of white population (slightly smaller in areas with good wind resource), and median rent (slightly lower in areas with good wind resource). We further investigate whether these three variables invalidate the exclusion restriction in Section A3.

- Table A7 shows results from the analysis on changes in political ideology. Using CCES data from 2006-2012, we recode questions on respondents' political ideology into dummy or ordinal variables, representing the share of liberal respondents and their ideology on a 5-point scale with 5 being "very liberal" and 1 being "very conservative." In Table A7, we find no evidence that political ideology is correlated with either wind turbine construction or wind potential at the congressional district level between 2006 and 2012.

Table A4: Balance Regression – Demographics

	(1) Pop	(2) White	(3) Foreign	(4) Male	(5) 65+
Mean wind potential * time	1.8492**	-0.0016*	0.0001	0.0001	0.0003
	(0.7664)	(0.0009)	(0.0001)	(0.0001)	(0.0002)
Observations	2009	2009	2009	2009	2009
Districts	287	287	287	287	287

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Balance Regression – Income

	(1) Med Inc	(2) PC Inc	(3) Med Rent	(4) Abv Poverty
Mean wind potential * time	-0.0207	-0.0312	-2.9939**	-0.0001
	(0.0600)	(0.0310)	(1.3053)	(0.0005)
Observations	2009	2007	2009	2009
Districts	287	287	287	287

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Balance Regression – Education and Employment

	(1) Avg Hrs	(2) Male AS+	(3) Female AS+	(4) Empl Ag	(5) Empl Manuf
Mean wind potential * time	-0.0109	-0.0002	-0.0002	-0.0001	0.0003
	(0.0113)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Observations	2009	2009	2009	2009	2009
Districts	287	287	287	287	287

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Balance Regression – Political Ideology

	Liberal (%)		Ideology (5-Point Scale)	
	(1) Model	(2) Model	(3) Model	(4) Model
Panel A: Reduced Form				
Mean wind potential * time	0.001	0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.005)	(0.005)
Panel B: OLS				
log(Cumulative capacity+1)	0.001		0.004	
	(0.002)		(0.006)	
log(Cumulative count+1)		0.002		0.008
		(0.002)		(0.006)
Panel C: IV				
log(Cumulative capacity+1)	0.005		-0.004	
	(0.013)		(0.033)	
log(Cumulative count+1)		0.005		-0.004
		(0.015)		(0.037)
Observations	2009	2009	2009	2009
Districts	287	287	287	287

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A4 Robustness

- Table A8 presents the results on electoral outcomes excluding California, which saw a wind energy boom already in the early 1980s. We want to ensure that the main results are not driven entirely by states that are traditionally both strongly favorable toward Democrats and have witnessed considerable growth in wind energy before our sample period. We see that while the estimated coefficients are slightly attenuated perhaps due to the decrease in sample size, they remain statistically significant and are qualitatively similar to those under the full sample.

- Tables A9 and A10 show that our election and environmental voting results are robust to excluding urban centers from the analysis. Since urban centers tend to be more Democratic, one may be concerned that the main results are driven by urban areas. Urbanized areas (UA) are defined by the 2000 Census[1] as core census blocks/block groups that have a population density of at least 1,000 people per square mile and surrounding census blocks with an overall density of at least 500 people per square mile. We calculate the total area of each congressional district that are classified as an UA by the Census Bureau, and we classify a congressional district as an "Urban District" if more than 50% of its area are urban. Our results are robust to the exclusion of urban centers. In fact, dropping the urban centers strengthens the effects of wind turbines on election outcomes and barely changes the environmental voting results. Along with Table A7, the evidence overwhelmingly suggests that our results are not driven by changing political ideology.

- In Table A11, we examine the robustness of results on electoral outcomes by creating a separate sample that includes Texas. Figure A2 shows there were significant congressional district boundary changes in Texas between the 108th and 109th congress (2003-2005). As a result, we exclude Texas in the main analysis to minimize the impact of endogenous boundary changes on electoral outcomes. In light of the boundary changes in Figure A2, we restrict the sample to the period 2005-2012 for this analysis. Our main results are robust to including Texas – a 100 MW increase in cumulative wind turbine capacity significantly increases the democratic vote share by 1.6 percentage points.

- In Tables A12 and A13, we show that our main election results are robust to clustering standard errors at the state level, instead of at the congressional district level (our main specification). Since there are relatively few clusters at the state level (25 states) in the sample, the cluster-robust standard errors assuming t-distribution may lead to over-rejections of the null hypothesis (Cameron, Gelbach and Miller 2008). As such, we also implement the wild bootstrap correction procedure from the `boottest` Stata program to calculate p-values and 95% confidence intervals of the coefficient estimate (Roodman et al. 2019). We find that the coefficient estimates are statistically significant under both the cluster-robust and wild bootstrap procedures.

- Tables A14 and A15 replicate the election and environmental voting regression results when the three balance variables (total population, share of white population, median gross rent), which were found to be significantly different across districts with and without wind resources, are included as controls. It shows that (i) our results remain unchanged if these variables are included as controls and (ii) the controls themselves are not correlated with wind energy deployment.

- Tables A16 and A17 replicate the election and environmental voting regression results using median and maximum wind potential respectively as the instrumental variable. We see that using other statistics of wind potential does not affect the results.

- Figure A3 examines the sensitivity of our main results for electoral outcomes when relaxing the instrument exclusion restriction. Each graph represents one set of regression results with the specified outcome variable (Democratic, Republican or incumbent vote share) and explanatory variable (cumulative capacity or count). We see that the confidence intervals are above zero for Democratic vote

[1] See here for details.

share, below zero for Republican vote share and around zero for incumbent vote share. In addition, the magnitudes for each regression are close to our point estimates except for the most extreme cases when γ is approaching 1. This provides further evidence for the validity of our IV approach.

- Table A18 tests the robustness of our results to changing the specification. Instead of our main specification, where the instrument is the mean wind potential of a district $\times$ time, here we implement a Bartik-type instrument, which uses the mean wind potential as a measure of share and interacting that with an election-year level measure of the installed wind turbine capacity in the whole country. Our main electoral results are robust to using a Bartik-type shift-share instrument.

Table A8: Election Outcomes Excluding California: OLS and IV Regression Results

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel A: OLS						
Cumulative capacity (MW)	0.006**		-0.006**		-0.002	
	(0.003)		(0.003)		(0.003)	
Cumulative count		0.011**		-0.011**		-0.003
		(0.005)		(0.005)		(0.005)
Panel B: IV						
Cumulative capacity (MW)	0.023**		-0.023**		0.012	
	(0.010)		(0.010)		(0.012)	
Cumulative count		0.039**		-0.039**		0.020
		(0.017)		(0.017)		(0.020)
Observations	931	931	931	931	838	838
Districts	234	234	234	234	232	232
R^2	0.89	0.89	0.89	0.89	0.73	0.73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district.

Table A9: Election Outcome Excluding Urban Areas: IV Regression Results

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel: IV						
Cumulative capacity (MW)	0.037**		-0.037**		0.020	
	(0.014)		(0.014)		(0.017)	
Cumulative count		0.062**		-0.062**		0.034
		(0.025)		(0.025)		(0.028)
Observations	770	770	770	770	689	689
Districts	193	193	193	193	193	193
R^2	0.83	0.83	0.83	0.83	0.62	0.62

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Urbanized areas (UA) are defined by the 2000 Census as core census blocks/block groups that have a population density of at least 1,000 people per square mile and surrounding census blocks with an overall density of at least 500 people per square mile. We calculate the total area of each congressional district that are classified as UA by the Census Bureau, and we classify a congressional district as an "Urban District" if more than 50% of its area are urban. The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district. Our results are robust to the exclusion of urban centers.

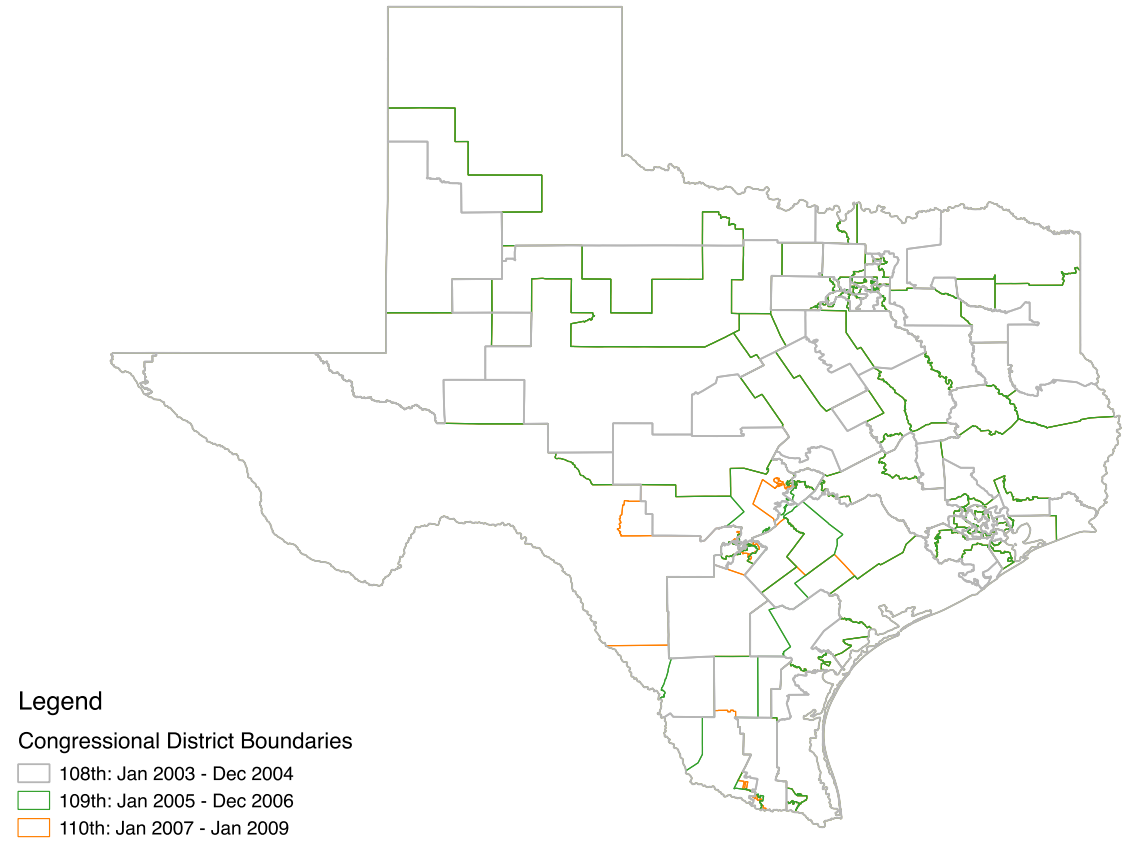
Table A10: Environmental Voting Outcome Excluding Urban Areas: IV Regression Results

	Pro-Environment Vote		Anti-Environment Vote	
	Model	Model	Model	Model
Panel: IV				
Cumulative capacity (MW)	0.025*		-0.030**	
	(0.013)		(0.014)	
Cumulative count		0.044**		-0.053**
		(0.022)		(0.024)
Observations	1929	1929	1929	1929
Districts	193	193	193	193
R^2	0.84	0.84	0.83	0.83

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Urbanized areas (UA) are defined by the 2000 Census as core census blocks/block groups that have a population density of at least 1,000 people per square mile and surrounding census blocks with an overall density of at least 500 people per square mile. We calculate the total area of each congressional district that are classified as UA by the Census Bureau, and we classify a congressional district as an "Urban District" if more than 50% of its area are urban. The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district. Our results are robust to the exclusion of urban centers.

Figure A2: Map of Texas Congressional District Boundary Changes



Notes: This map shows district boundaries in Texas for the 108th, 109th, and 110th congress. There were significant boundary changes due to redistricting and gerrymandering between 2003 and 2005. As a result, we exclude Texas in the main analysis sample to minimize the impact of endogenous boundary changes on electoral outcomes.

Table A11: Election Outcome Including Texas: OLS and IV Regression Results

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel A: OLS						
Cumulative capacity (MW)	0.001		-0.001		-0.003**	
	(0.002)		(0.002)		(0.001)	
Cumulative count		0.002		-0.002		-0.004***
		(0.003)		(0.003)		(0.002)
Panel B: IV						
Cumulative capacity (MW)	0.016**		-0.016**		0.000	
	(0.008)		(0.008)		(0.006)	
Cumulative count		0.026**		-0.026**		0.001
		(0.013)		(0.013)		(0.010)
Observations	1271	1271	1271	1271	1160	1160
Districts	319	319	319	319	317	317
R^2	0.87	0.87	0.87	0.87	0.69	0.69

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district.

Table A12: Election Outcome: Cluster-Robust Standard Error by State

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel A: OLS						
Cumulative capacity (MW)	0.006*		-0.006*		-0.002	
	(0.003)		(0.003)		(0.003)	
Cumulative count		0.011**		-0.011**		-0.004
		(0.005)		(0.005)		(0.004)
Panel B: IV						
Cumulative capacity (MW)	0.030**		-0.030**		0.008	
	(0.011)		(0.011)		(0.013)	
Cumulative count		0.050**		-0.050**		0.013
		(0.019)		(0.019)		(0.021)
Observations	1143	1143	1143	1143	1038	1038
States	25	25	25	25	24	24
R^2	0.88	0.88	0.88	0.88	0.73	0.73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: We examine the robustness of our main electoral results to clustering standard errors at the state level, instead of at the congressional district level (our main specification). The instrument is the product of the time trend with the average wind power resource. We include district and state-year fixed effects and cluster standard errors by states.

Table A13: Election Outcome: Wild Bootstrap Standard Error by State

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel: IV						
Cumulative capacity (MW)						
Estimate	0.030		-0.030		0.008	
Cluster-robust by state, standard error	(0.011)		(0.011)		(0.013)	
Wild bootstrap by state, p-value	<0.010>		<0.000>		<0.591>	
Wild bootstrap by state, confidence interval	[0.010, 0.060]		[-0.058, -0.011]		[-0.015, 0.062]	
Cumulative count						
Estimate		0.050		-0.050		0.013
Cluster-robust by state, standard error		(0.019)		(0.019)		(0.022)
Wild bootstrap by state, p-value		<0.002>		<0.004>		<0.535>
Wild bootstrap by state, confidence interval		[0.019, 0.100]		[-0.099, -0.014]		[-0.025, 0.095]

Notes: We examine the robustness of our main electoral results to clustering standard errors at the state level, instead of at the congressional district level (our main specification). Here we compare the cluster-robust standard errors by state and the wild bootstrap p-values and 95% confidence intervals. The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects.

Table A14: Election Outcome Including Balance Variables: IV Regression Results

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel: IV						
Cumulative capacity (MW)	0.026*		-0.026*		0.024	
	(0.014)		(0.014)		(0.016)	
Cumulative count		0.046*		-0.046*		0.041
		(0.024)		(0.024)		(0.027)
Total population (thousand)	-0.014	-0.014	0.014	0.014	0.054*	0.055*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.031)	(0.031)
White (%)	-28.099	-27.829	28.099	27.829	-7.256	-6.817
	(23.298)	(23.336)	(23.298)	(23.336)	(19.174)	(19.198)
Median gross rent ($)	0.032*	0.032*	-0.032*	-0.032*	0.015	0.015
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
Observations	856	856	856	856	765	765
Districts	287	287	287	287	279	279
R^2	0.90	0.90	0.90	0.90	0.78	0.78

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district.

Table A15: Environmental Voting Outcome Including Balance Variables: IV Regression Results

	Pro-Environment Vote		Anti-Environment Vote	
	(1) Model	(2) Model	(3) Model	(4) Model
Panel: IV				
Cumulative capacity (MW)	0.024*		-0.023*	
	(0.013)		(0.013)	
Cumulative count		0.043*		-0.041*
		(0.022)		(0.023)
Total population (thousand)	-0.013	-0.013	0.023	0.023
	(0.031)	(0.030)	(0.026)	(0.026)
White (%)	-14.963	-14.069	4.569	3.705
	(18.999)	(19.014)	(16.529)	(16.534)
Median gross rent ($)	-0.000	-0.000	-0.017	-0.017
	(0.016)	(0.016)	(0.016)	(0.016)
Observations	2007	2007	2007	2007
Districts	287	287	287	287
R^2	0.87	0.87	0.88	0.88

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district.

Table A16: Election Outcome: Comparison of Different Instruments

	Democratic Vote		Republican Vote		Incumbent Vote	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
IV: Median						
Cumulative capacity (MW)	0.028**		-0.028**		0.022	
	(0.013)		(0.013)		(0.015)	
Cumulative count		0.047**		-0.047**		0.037
		(0.023)		(0.023)		(0.026)
IV: Maximum						
Cumulative capacity (MW)	0.009		-0.009		-0.017	
	(0.016)		(0.016)		(0.014)	
Cumulative count		0.015		-0.015		-0.028
		(0.026)		(0.026)		(0.024)
Observations	1143	1143	1143	1143	1038	1038
Districts	287	287	287	287	285	285
R^2	0.89	0.89	0.89	0.89	0.73	0.73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Environmental Voting Outcome: Comparison of Different Instruments

	Pro-Environment Vote		Anti-Environment Vote	
	(1) Model	(2) Model	(3) Model	(4) Model
*IV: Median wind potential * time*				
Cumulative capacity (MW)	0.027*		-0.041**	
	(0.014)		(0.017)	
Cumulative count		0.047*		-0.072**
		(0.025)		(0.029)
*IV: Max wind potential * time*				
Cumulative capacity (MW)	0.028		-0.027	
	(0.019)		(0.019)	
Cumulative count		0.049		-0.048
		(0.033)		(0.034)
Observations	2868	2868	2868	2868
Districts	287	287	287	287
R^2	0.86	0.86	0.87	0.87

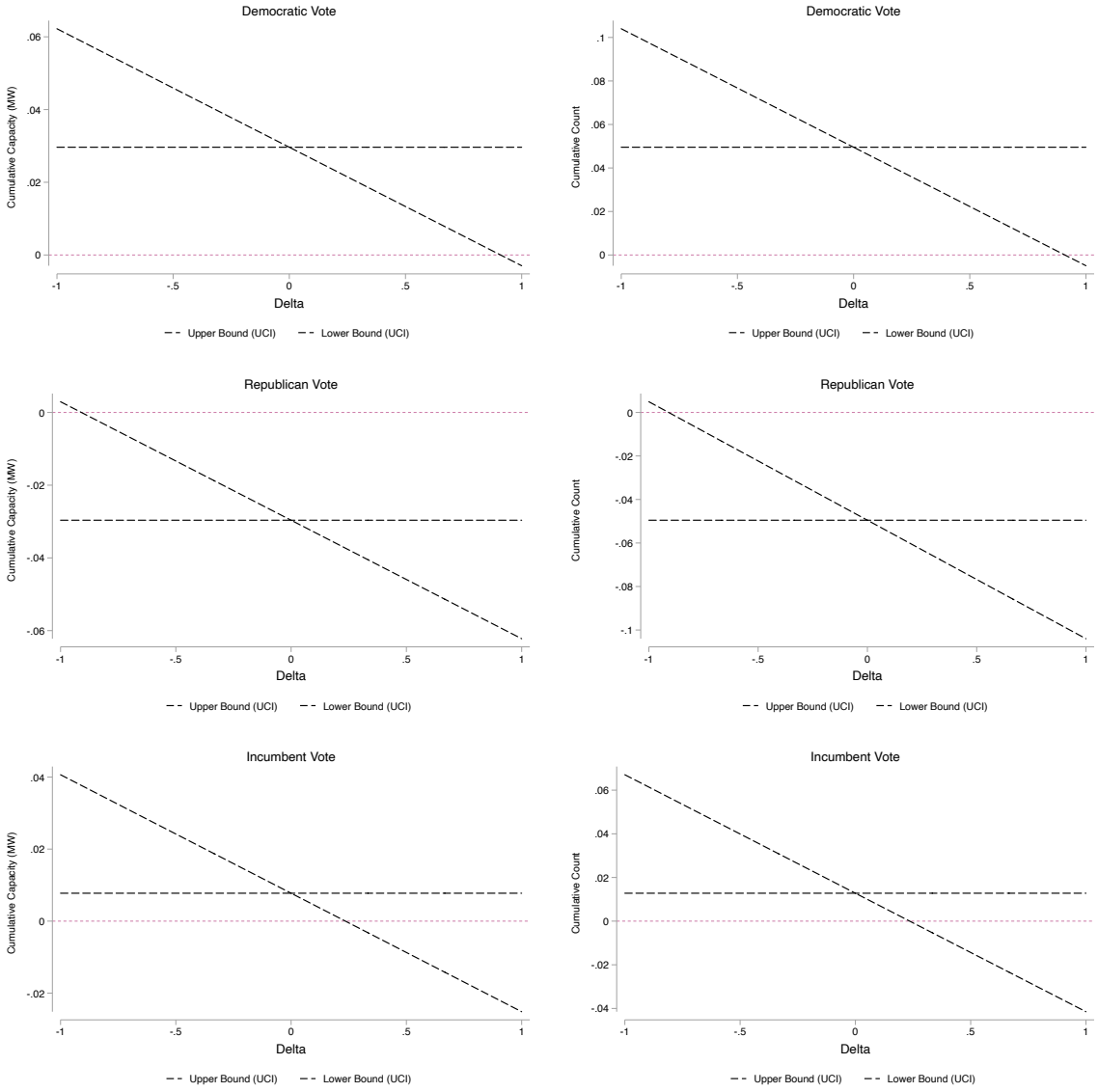
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A18: Election Outcome: Bartik-Type Instrument

	Democratic Vote		Republican Vote		Incumbent Vote	
	Model	Model	Model	Model	Model	Model
*IV: Mean wind potential * National wind capacity*						
Cumulative capacity (MW)	0.032**		-0.032**		0.007	
	(0.013)		(0.013)		(0.013)	
Cumulative count		0.052**		-0.052**		0.011
		(0.021)		(0.021)		(0.021)
Observations	1143	1143	1143	1143	1038	1038
States	287	287	287	287	285	285
R^2	0.88	0.88	0.88	0.88	0.73	0.73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A3: Sensitivity Analysis of the Instrument Exclusion Restriction



Notes: These figures show results from the sensitivity analysis of the instrument exclusion restriction using the union of confidence interval method as described in Conley et al. (2012). 95% confidence intervals of estimated coefficients from IV regression.

A5 Turnout by Partisanship

- Table A19 explores whether the construction of wind turbines has led to a differential increase in voter turnout across Democratic, Republican, and Independent voters. We use cross-sectional survey data from the American National Election Studies (ANES) for the presidential elections 2004 and 2008 (other presidential elections are outside our sample; we do not have survey data for midterm elections). The survey data are from a collaboration by Stanford University and University of Michigan. For our purposes, they are useful because they contain information about party identification, voting, and congressional district. For more information, see `http://www.electionstudies.org/`.
- For each district-year (2004 or 2008), we then code each respondent as Democratic, Republican, or Independent based on a 7-point party identification scale (1-3 D; 4-5 I, 6-7 R). For each of the three categories, we then calculate the share (0-1) of respondents who report voting in that year's presidential and congressional election.
- The ANES sample contains voter turnout data for 142 districts within 23 states for a total of 162 state-district-year observations. Because the number of observations is small, the instrumental variable analysis now only includes state and year fixed effects. If we were to include district and/or state-election fixed effects, we would lose the vast majority of our observations.
- The results show that there is no evidence for a change in turnout depending on partisanship. Combined with the results on overall turnout presented in the main text, we see that it is unlikely windmills have mobilized new voters to vote in favor of Democrats.

Table A19: Voter Turnout by Party Identification Robustness Check: First Stage and IV Regression Results

	Democratic Turnout		Republican Turnout		Independent Turnout	
	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
Panel A: First stage						
Mean wind potential * time	0.357**	0.352*	0.346*	0.354	0.394*	0.375
	(0.175)	(0.187)	(0.202)	(0.216)	(0.218)	(0.237)
Panel B: IV						
log(Cumulative capacity+1)	-0.048		-0.037		0.103	
	(0.046)		(0.063)		(0.123)	
log(Cumulative count+1)		-0.048		-0.036		0.108
		(0.047)		(0.062)		(0.130)
Observations	145	145	125	125	84	84
Districts	127	127	112	112	76	76
R^2	0.20	0.20	0.07	0.06	0.12	0.08

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. Data on voter turnout by party identification comes from the American National Election Studies (ANES) for the presidential elections 2004 and 2008 (other presidential elections are outside our sample; we do not have survey data for midterm elections). Because the number of observations is small, the instrumental variable analysis now only includes state and year fixed effects. Standard errors are clustered by district.

A6 Additional Analysis: Legislator Fixed Effects

- Table A20 replicate the environmental policy analysis with legislator fixed effects included. The results show that when the electoral effects are removed and we only focus on changes in the behavior of legislators, the effect of wind turbine construction on environmental voting outcomes are significantly weakened, with smaller and less precisely estimated coefficients. This suggests that wind turbine construction mostly shape legislative behavior through elections: pro-renewables candidates gain an advantage over their anti-renewables candidates.

Table A20: Environmental Voting Outcome Robustness Check Including Legislator Fixed Effects: OLS and IV Regression Results

	Pro-Environment Vote		Anti-Environment Vote	
	(1) Model	(2) Model	(3) Model	(4) Model
Panel A: OLS				
log(Cumulative capacity+1)	0.350		-0.453	
	(0.472)		(0.438)	
log(Cumulative count+1)		0.394		-0.544
		(0.539)		(0.510)
Panel B: IV				
log(Cumulative capacity+1)	1.356		-3.504*	
	(1.854)		(1.802)	
log(Cumulative count+1)		1.539		-3.979*
		(2.109)		(2.067)
Observations	2860	2860	2860	2860
Districts	287	287	287	287
R^2	0.95	0.95	0.96	0.96

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. All models include district and state-year fixed effects. Standard errors are clustered by district.

A7 Additional Analysis: Placebo Tests

- In Table A21, we conduct a placebo test on the environmental policy analysis. We first restrict the sample to only districts with no wind turbine installed between 2004-2012 and then estimate the reduced form model of environmental voting outcomes on the instrumental variable. If the exclusion restriction holds, we would expect the instrument to have no effect on voting outcomes in districts without windmills. Indeed, the results show that the instrument has no explanatory power on pro- or anti-environmental vote shares in districts without wind turbines. This further suggests that our instrument, mean wind potential, only affects voting outcomes through wind turbine construction.

Table A21: Environmental Voting Outcome Placebo Test: Reduced Form Results

	(1) Pro-Environment Vote	(2) Anti-Environment Vote
Mean wind potential * time	-0.114	-0.204
	(0.499)	(0.596)
Observations	1713	1713
Districts	239	239
R^2	0.88	0.89

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The instrument is the product of the time trend with the average wind power resource. Here we restrict the analysis to only districts without any wind turbine constructed during the sample period of 2004-2012. All models include district and state-year fixed effects. Standard errors are clustered by district.

A8 Additional Analysis: Changes in Public Opinion on the Environment

- In Table A22, we check if wind power affects public opinion on the environment. Using CCES data from 2006-2012, we identify two variables related to the environment that are consistently asked across the years. The variables measure the extent to which 1) the environment is more important than jobs (Environment v. Job) and 2) global warming is happening and action warranted (Global Warming). We code these two survey questions as dummies (Panel A) and ordinal variables (Panel B), with 1 or higher values (on scales of 1 to 5 for Environment v. Job and 1 to 4 for Global Warming) representing more pro-environment opinions respectively.
- The specification follows our main IV model, where the instrument is the product of time trend and the average wind potential for each district and the endogenous variable is the cumulative wind power installed. We find no evidence that having more wind turbines affects public opinion toward the environment at the congressional district level. The coefficients are imprecise for both environmental opinion outcomes and regardless of whether we treat them as dummy or ordinal variables.

Table A22: Public Opinion on the Environment: IV Regression Results

	Environment v. Job		Global Warming	
	(1) Model	(2) Model	(3) Model	(4) Model
Panel A: Dummy Dependent Var				
log(Cumulative capacity+1)	-0.023		0.018	
	(0.015)		(0.025)	
log(Cumulative count+1)		-0.026		0.020
		(0.017)		(0.028)
Observations	1435	1435	1721	1721
Districts	287	287	287	287
R^2	0.67	0.67	0.62	0.62
Panel B: Ordinal Dependent Var				
log(Cumulative capacity+1)	-0.029		0.003	
	(0.039)		(0.049)	
log(Cumulative count+1)		-0.033		0.003
		(0.044)		(0.055)
Observations	1435	1435	1721	1721
Districts	287	287	287	287
R^2	0.82	0.82	0.71	0.71

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effect of wind turbine construction on public opinion toward the environment using two variables from the CCES between 2006-2012. The variables measure the extent to which 1) the environment is more important than jobs (Environment v. Job) and 2) global warming is happening and action is warranted (Global Warming). We code these two survey questions as dummies (Panel A) and ordinal variables (Panel B), with 1 or higher values (on scales of 1 to 5 for Environment v. Job and 1 to 4 for Global Warming) representing more pro-environment opinions respectively. We use the product of time trend with the average of wind potential to instrument for wind power installation. All models include district and state-year fixed effects. Standard errors are clustered by district.

A9 Additional Analysis: Event Study of Renewable Portfolio Standard

- In this section, we conduct an event study to examine the impact of mandatory state-wide Renewable Portfolio Standard (RPS) on wind turbine construction and voting outcomes.
- To examine the post-RPS slope change, we estimate a trend break model, where i is state, j is district and t is year. y_{ijt} represent cumulative wind turbine construction or voting outcomes. Event time E_{it} is defined as year minus the mandatory RPS adoption year for a given state. RPS_{it} is a dummy variable equal to one for years after RPS adoption and is interacted with event time E_{it}. We include state fixed effects and state-specific time trends to account for both time-invariant unobservables for each state and linear trends in the growth of wind turbines or electoral outcomes.

$$y_{ijt} = \alpha_i + \beta_{it} + \gamma RPS_{it} \times E_{it} + \varepsilon_{ijt}. \tag{2}$$

- In addition to the linear trend break model, we also estimate the average effect over the entire post-RPS period, where γ measures the average post-RPS change in outcomes.

$$y_{ijt} = \alpha_i + \beta_{it} + \gamma RPS_{it} + \varepsilon_{ijt}. \tag{3}$$

- Table A23 shows that the adoption of RPS has significantly increased the number and installed capacity of wind turbines. This, in turn, has led to an increase in the vote share of Democratic candidates in congressional elections, an overall increase in pro-environmental issue voting, and a large increase in pro clean energy votes. These results are consistent with our main finding that wind turbine construction generates large electoral benefits for Democratic candidates.

Table A23: Renewable Portfolio Standard and Wind Turbine Construction

	A. Linear Trend Break			
	(1) Capacity (MW)	(2) Count	(3) Log Capacity	(4) Log Count
RPS × Event Time	13.580***	7.436**	0.100***	0.089***
	(4.495)	(3.078)	(0.023)	(0.020)
Observations	4696	4696	4696	4696
States	28	28	28	28
R^2	0.09	0.06	0.20	0.16
	B. Average Effect			
	Capacity (MW)	Count	Log Capacity	Log Count
RPS	37.996**	20.129**	0.422***	0.383***
	(13.727)	(9.120)	(0.115)	(0.107)
Observations	4696	4696	4696	4696
States	28	28	28	28
R^2	0.08	0.06	0.19	0.15

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Event study of state-wide mandatory Renewable Portfolio Standard and wind turbine construction. Both trend break and average effect models control for state-specific time trends and state fixed effects. Robust standard errors are clustered at the state level.

Table A24: Renewable Portfolio Standard and Electoral Outcomes

	A. Linear Trend Break		
	(1) Democratic Vote	(2) Republican Vote	(3) Incumbent Vote
RPS × Event Time	0.205*	-0.335***	-0.441*
	(0.115)	(0.118)	(0.228)
Observations	4696	4696	4150
States	28	28	28
R^2	0.11	0.11	0.10
	B. Average Effect		
	Democratic Vote	Republican Vote	Incumbent Vote
RPS	4.386***	-4.472***	-1.106
	(1.202)	(1.188)	(1.450)
Observations	4696	4696	4150
States	28	28	28
R^2	0.11	0.11	0.10

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Event study of state-wide mandatory Renewable Portfolio Standard and electoral outcomes. Both trend break and average effect models control for state-specific time trends and state fixed effects. Robust standard errors are clustered at the state level.

Table A25: Renewable Portfolio Standard and Environmental Voting Outcomes

	A. Linear Trend Break		
	(1) Pro-Environment Vote	(2) Pro Clean Energy Vote	(3) Anti-Environment Vote
RPS × Event Time	-0.274	1.413***	-0.407
	(0.225)	(0.429)	(0.263)
Observations	9682	6245	9682
States	28	28	28
R^2	0.18	0.12	0.18
	B. Average Effect		
	Pro-Environment Vote	Pro Clean Energy Vote	Anti-Environment Vote
RPS	4.640***	11.146***	-7.658***
	(1.050)	(3.635)	(1.139)
Observations	9682	6245	9682
States	28	28	28
R^2	0.18	0.12	0.18

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Event study of state-wide mandatory Renewable Portfolio Standard and environmental voting outcomes. Both trend break and average effect models control for state-specific time trends and state fixed effects. Robust standard errors are clustered at the state level.

A10 Additional Description: Content Analysis

- We use data from Voxgov between 2003-2012 that contains press releases of House of Representatives with the keyword "wind" and are classified under the category "Energy/Environment, Natural Resources". The unit of analysis is a press release (r) with full text of its content, year and month of issuance, congress, state and level of government, and name and other demographic information of the legislator. By matching these press release data with the name of legislators in our congressional election and environmental voting datasets, we can identify the state (i) and district (j) the legislator is from, his/her party affiliation, and year (t) the press release is issued.

- We conduct the text analysis using Structural Topic Model (STM) to identify 20 topics. The STM decomposes each press release into a mixture of multiple topics. The topical prevalence represents how much each topic contributes to a press release with the topic proportion across all topics summing to 1. While the number of topics is the most important user input to the topic model, the STM documentation says: "there is no right answer to the appropriate number of topics. More topics will give more fine-grained representations of the data at the potential cost of being less precisely estimated" (Roberts et al. 2013, 2014, 2016, 2019). Since our corpus includes less than 5000 press releases that focus on a narrowly defined topic "wind," we choose 20 topics for parsimony. We also employ a data-driven approaching using the `searchK` function, which computes diagnostic properties of the model under different topic numbers, to evaluate the optimal number of topics. The visual diagnostics are available upon request. Word clouds associated with the 20 topics and the most common five words associated with each topic are not shown here due to space constraints and are available upon request.

- We model topic prevalence as a function of the interaction between legislator partisanship Party_{rijt} and the cumulative installed capacity of wind turbines Capacity_{rijt}. We enter the covariates additively and include a flexible spline function in year to allow for a nonlinear relationship between the year that press releases are published and the topic prevalence. To initialize the model, we use the default "spectral" option, which is based on the method of moments, is deterministic and stable, and produces the best results consistently compared to other approaches (Roberts et al. 2019).

A11 Methods for Employment Outcomes

- We collect annual business establishment data from the census County Business Pattern (CBP). The data is available by county and 6-digit NAICS industry codes. Variables consist of the number of establishments, employment during the week of March 12, first quarter payroll, and annual payroll.

- To merge the CBP data with our main panel, we use a cross-walk relationship file between county FIPS codes and 111th Congressional District (2009-2010) codes created by the Missouri Census Data Center.[2] We are able to use the 111th Congress for the whole sample period of 2003-2012, because district boundaries are largely unchanged during this time.

- A technical difficulty arises because a county could belong to multiple congressional districts. We allocate county-level variables in the CBP data to districts using the allocation factor variable in the cross-walk file, which sums to 1 for each county and represents the portion of each county belonging to the associated districts.

- The CBP withheld employment and payroll data in some cases to protect the confidentiality of individual employers. In such cases, the original variables are replaced with zeroes and a new variable flags the data suppression and indicates the employment class size. To fill in the missing values, we use the lower bound for each employment class size as a conservative way to impute the data. For example, if an industry has employment class size "500-999", we would replace the employment variable with 500.

[2] Available here: `http://mcdc.missouri.edu/websas/geocorr12.html`

- Since the CBP data is for mid-March and likely reflect the economic conditions of the previous year, we lag the year variable by 1 when merging with the main panel. This means CBP data in 2004-2013 corresponds to 2003-2012 data for our main panel.
- We focus on three wind-related industries in the analysis: wind power structure construction, wind electric power generation and wind turbine manufacturing. Table A26 shows the NAICS code changes over time for these industries. For power generation, since the sub-category for wind electric began in 2012, we aggregate solar, wind, geothermal, biomass and other electric power generation industries in 2012 for backward consistency.

Table A26: NAICS Code Changes by Year for Wind-Related Industries

1997	2002	2007	2012	Industry Name
234930	237130	237130	237130	Wind power structure construction
221119	221119	221119	221115	Power generation, wind electric
333611	333611	333611	333611	Wind turbines (i.e., windmill) manufacturing