Wildfire Smoke and Voting Behavior in the United States[*]

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Abstract

Does wildfire smoke exposure shift political behavior? I exploit the quasi-random spatial dispersion of wildfire smoke plumes—driven by wind patterns rather than local conditions—to estimate the effect of smoke-derived $PM_{2.5}$ on county-level presidential and House election voting. Using daily county-level wildfire smoke $PM_{2.5}$ estimates (Childs et al., 2022) merged with election returns across multiple cycles (2008–2020 for presidential, 2016–2020 for House), I find that higher pre-election smoke exposure increases the Democratic two-party vote share and decreases the incumbent party's vote share. A 10 $\mu g/m^3$ increase in mean smoke $PM_{2.5}$ over the 60 days before the election is associated with a 0.9 percentage point increase in the Democratic vote share in presidential races. The incumbent punishment effect is roughly four times larger. Effects are present across the partisan spectrum but somewhat stronger in Democratic-leaning counties. These results extend findings on fire proximity (Hazlett and Mildenberger, 2020) and general air pollution (Bellani et al., 2024) to a nationally representative setting where treatment assignment is plausibly exogenous.

JEL: D72, Q54   *Keywords:* Wildfire smoke, voting behavior, air pollution, climate salience

1   Introduction

Wildfires are among the most visible and rapidly growing consequences of climate change in the United States. Between 2006 and 2020, wildfire smoke affected every region of the

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country, with dramatic intensification in the final years of the sample. Unlike ambient air pollution, wildfire smoke events are visible, sudden, and directly attributable to a specific cause—making them potentially more salient as signals of climate change. A growing literature investigates whether environmental shocks alter political behavior: Hazlett and Mildenberger (2020) find that proximity to California wildfires increases pro-environment voting, but only in already-Democratic areas; Bellani et al. (2024) show that overall PM_{10} pollution on election day shifts German voters against the incumbent; and Gomez et al. (2007) demonstrate that rain suppresses voter turnout.

This paper bridges these strands by using *wildfire-specific* smoke $PM_{2.5}$ as a treatment variable across the entire continental United States. Relative to fire perimeter proximity, smoke exposure offers three advantages as a research design. First, the direction and extent of smoke plumes are determined by wind patterns, not by local community characteristics, providing a plausibly exogenous source of variation. Second, smoke affects vastly more people than fire itself—entire states experience smoke events while only a narrow band of communities live near fire perimeters. Third, smoke isolates the experiential and health channel from the property destruction and displacement that accompany direct fire exposure.

2 Data

Wildfire smoke $PM_{2.5}$. I use daily county-level estimates of wildfire-attributed $PM_{2.5}$ from Childs et al. (2022), covering all U.S. counties from January 2006 through December 2020. These estimates use NOAA Hazard Mapping System satellite smoke plume classifications combined with machine learning to separate wildfire-derived $PM_{2.5}$ from background pollution. The data are available at Harvard Dataverse (doi:10.7910/DVN/DJVMTV).

Election returns. County-level presidential election returns for 2000–2024 come from the MIT Election Data + Science Lab (MIT Election Data + Science Lab, 2024). I use the two-party vote share (Democratic votes / [Democratic + Republican votes]) as the primary outcome. For House elections, I use precinct-level returns with county identifiers (2016, 2018, 2020) from the same source, aggregating precinct votes to the county level to enable analysis at the same geographic unit as the presidential regressions.

Analysis samples. The overlap of smoke data (2006–2020) and presidential elections yields four election cycles: 2008, 2012, 2016, and 2020. After merging on county FIPS codes, the presidential analysis sample contains 12,429 county-election observations spanning 3,108 counties. The county-level House sample covers three election cycles (2016, 2018,

2020) with 9,171 county-election observations.

Smoke exposure measures.   For each county and election, I aggregate daily smoke $PM_{2.5}$ over pre-election windows: 7, 30, 60, and 90 days before election day, plus the full fire season (June 1 to election day). The primary treatment variable is the mean daily smoke $PM_{2.5}$ in the 60 days before the election.

3   Empirical Strategy

I estimate two-way fixed effects models of the form:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot \text{SmokePM}_{ct} + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is the outcome in county c in election year t, α_c are county fixed effects absorbing all time-invariant county characteristics, γ_t are election-year fixed effects absorbing national swings, and SmokePM_{ct} is the mean wildfire smoke $PM_{2.5}$ in the pre-election window. Standard errors are clustered by county.

Identifying assumption.   The key assumption is that, conditional on county and year fixed effects, variation in wildfire smoke exposure is uncorrelated with unobserved determinants of voting. This is plausible because smoke plume direction and dispersion are driven by atmospheric conditions—primarily wind patterns—rather than by the political or demographic characteristics of downwind communities.

Threats to identification.   Two potential concerns merit discussion. First, spatially correlated shocks such as drought could affect both fire activity and local economic conditions. This is mitigated by the fact that smoke travels hundreds of miles from fire origins, so downwind counties experience smoke without experiencing the local conditions that generated the fires. Second, secular trends in fire-prone versus non-fire-prone regions could confound the estimates; county fixed effects absorb level differences, and year fixed effects absorb national trends, but region-specific trends remain a potential concern.

Continuous treatment and TWFE.   Recent work by Callaway et al. (2024) shows that TWFE regressions with a continuous treatment variable can produce coefficients with ambiguous causal interpretation due to heterogeneous weighting across dose levels. In our setting, several features mitigate these concerns: treatment is atmospherically assigned (limiting selection into dose levels), and we estimate a linear slope corresponding to the average

causal response (ACRT) decomposition in which weights are non-negative. As a robustness check, I verify that results are qualitatively similar when the treatment is dichotomized or discretized into dose bins.

4 Results

4.1 Main Results

Table 1 presents the main presidential election estimates. Column (1) shows that a 1 $\mu g/m^3$ increase in mean smoke $PM_{2.5}$ over the 60 days before the election increases the Democratic two-party vote share by 0.087 percentage points ($p < 0.001$). At the sample mean of 2.7 $\mu g/m^3$, this implies that moving from zero smoke to mean exposure shifts the Democratic vote share by roughly 0.24 percentage points. A county experiencing the 2020 Western fire season levels of smoke ($\sim$40 $\mu g/m^3$) would see a shift of approximately 3.5 percentage points.

Column (2) shows that the incumbent punishment effect is substantially larger: a 1 $\mu g/m^3$ increase reduces the incumbent party's vote share by 0.40 percentage points. This is consistent with the negative-affect mechanism identified by Bellani et al. (2024) in the German context—smoke makes voters feel worse, and they punish the party in power regardless of its partisan identity.

Table 1: Effect of Wildfire Smoke on Presidential Voting Outcomes

	(1) DEM Vote Share	(2) Incumbent Vote Share	(3) Log Total Votes
Mean Smoke $PM_{2.5}$ (60d)	0.00087***	−0.00399***	0.00242***
	(0.00009)	(0.00044)	(0.00018)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	12,429	12,429	12,429
R^2 (within)	−0.007	−0.024	0.070

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered by county.

4.2 Heterogeneity by Prior Partisanship

Table 2 splits the sample by terciles of lagged Democratic vote share. The pro-Democratic shift from smoke is present in all three groups, with a somewhat larger effect in D-leaning counties (0.082 pp) than in R-leaning counties (0.066 pp). Unlike Hazlett and Mildenberger (2020), who find effects *only* in Democratic areas for fire proximity, I find that smoke exposure

moves all county types toward the Democrats, though the effect is modestly larger where pro-environment attitudes are presumably more prevalent.

Table 2: Heterogeneity by Prior Partisanship

	R-Leaning	Swing	D-Leaning
Mean Smoke PM$_{2.5}$ (60d)	0.00066***	0.00049***	0.00082***
	(0.00021)	(0.00014)	(0.00013)
Observations	4,144	4,141	4,143

*** $p < 0.01$. County and year FE. SEs clustered by county.

4.3 Temporal Dynamics

Figure 1 plots the estimated effect of mean smoke PM$_{2.5}$ on Democratic vote share across different pre-election windows. The effect is statistically significant at all windows, with the largest point estimate at the 30-day window. This suggests that smoke exposure in the weeks most proximate to the election has the greatest electoral impact, consistent with a salience or recency mechanism.
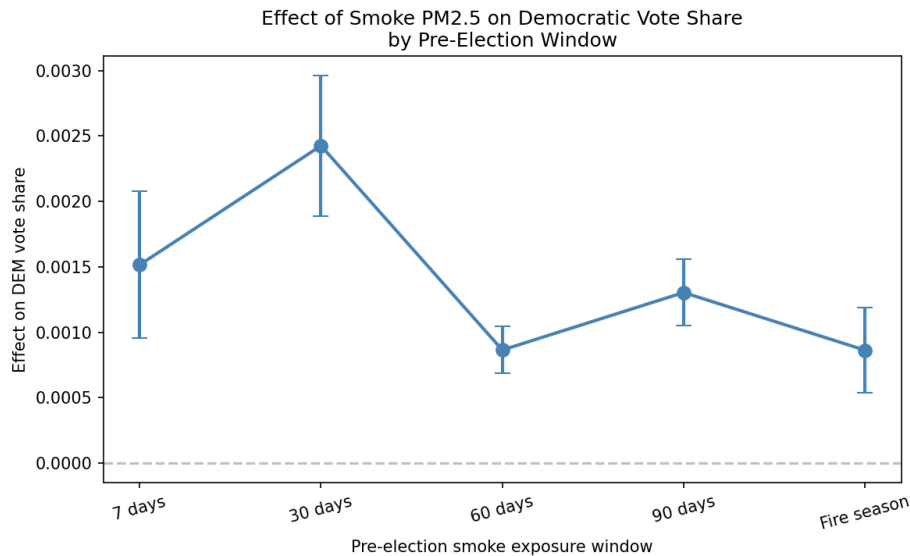

Figure 1: Effect of smoke PM$_{2.5}$ on Democratic vote share by pre-election window length. Points are coefficient estimates from separate TWFE regressions; bars are 95% confidence intervals.

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4.4 Geographic Variation in Smoke Exposure

Figure 2 displays county-level mean smoke $PM_{2.5}$ in the 30 days before each election. The maps illustrate both the geographic scope and temporal variation that identify the main estimates: 2016 saw minimal pre-election smoke nationwide, while 2020 produced extreme exposure across the Western states following the historic August–September fire season.
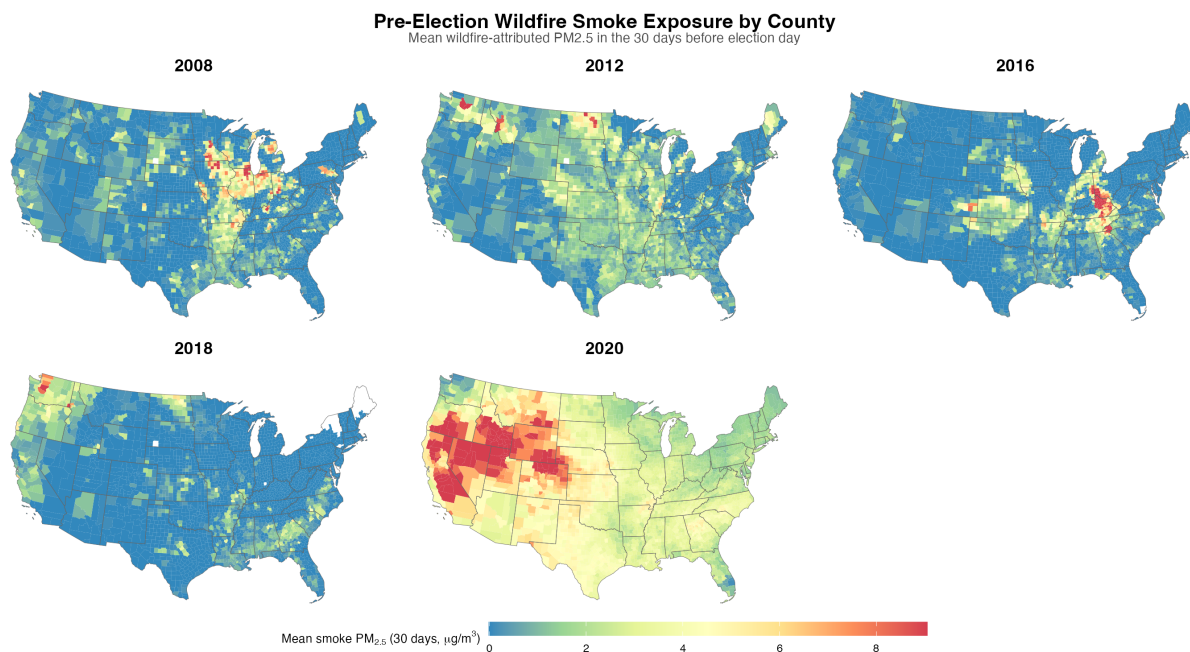

Figure 2: Pre-election wildfire smoke exposure by county, 30-day window before election day. Color scale is identical across all panels.

4.5 House Elections

To test whether the effects extend beyond presidential races, I aggregate MEDSL precinct-level House returns (which include county FIPS identifiers) directly to the county level for 2016–2020, avoiding the measurement error that would be introduced by a county-to-congressional-district crosswalk.

Table 3 presents the county-level House results alongside the presidential estimates, all using the 60-day mean smoke $PM_{2.5}$ treatment. The county-level House analysis covers ap-

proximately 3,000 counties per election across three cycles (2016, 2018, 2020). Multi-district counties have votes from all House races aggregated, measuring overall House candidate performance in each county rather than individual district outcomes. The pro-Democratic and anti-incumbent effects are both statistically significant, though smaller in magnitude than the presidential estimates, consistent with the more candidate-driven nature of House races.

Table 3: Effect of Wildfire Smoke: County-Level House vs. Presidential

	(1) County House	(2) Presidential
Panel A: DEM Vote Share		
Mean Smoke $PM_{2.5}$ (60d)	0.00038***	0.00087***
	(0.00013)	(0.00009)
Panel B: Incumbent Vote Share		
Mean Smoke $PM_{2.5}$ (60d)	-0.00153***	-0.00399***
	(0.00045)	(0.00044)
Panel C: Log Total Votes		
Mean Smoke $PM_{2.5}$ (60d)	0.00177***	0.00242***
	(0.00066)	(0.00018)
Unit	County	County
FE	County + Year	County + Year
Observations	8,391 / 9,165	12,429
Elections	2016–2020	2008–2020

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. SEs clustered by county.
Panels A–B use contested races only; Panel C includes all.

As a further robustness check, I also estimate the House specifications at the congressional district level using Census county-to-district crosswalks (Appendix Table A1). The district-level estimates are noisier due to the measurement error introduced by the crosswalk, but the anti-incumbent effect remains statistically significant.

5 Discussion

Three mechanisms could drive these results. First, a *salience* channel: smoke makes climate change tangible, increasing the weight voters place on environmental issues and benefiting the party perceived as more pro-environment (Hazlett and Mildenberger, 2020; Kahn, 2007). Second, a *negative affect* channel: smoke degrades well-being and mood, and voters punish incumbents for experienced discomfort regardless of policy responsibility (Bellani et al., 2024;

Healy and Malhotra, 2010). Third, a *disruption* channel: smoke could differentially suppress turnout among certain voter groups (Gomez et al., 2007; Burke et al., 2022).

The data are more consistent with the first two mechanisms than the third. The pro-Democratic shift points toward salience, while the larger anti-incumbent effect points toward negative affect. The positive turnout coefficient (Column 3 of Table 1) is surprising and may reflect confounding from 2020's historically high turnout; this result should be interpreted cautiously.

Limitations. This proof of concept has several limitations that subsequent work should address. The analysis covers only four presidential elections and three House elections. The turnout measure (log total votes) is a crude proxy without a proper population denominator. County-level aggregation may mask within-county heterogeneity. And the negative within-R^2 values in some specifications suggest that the smoke variable alone explains limited within-county variation after absorbing fixed effects, underscoring that these are small effects on a noisy outcome.

6   Conclusion

Wildfire smoke exposure shifts votes toward the Democratic Party and against the incumbent in both presidential and House elections, with effects that are statistically significant, present across the partisan spectrum, and strongest in the weeks immediately preceding the election. These preliminary results suggest that wildfire smoke—which is plausibly exogenous and affects a far larger population than fire proximity—offers a compelling research design for studying how environmental experience shapes political behavior.

References

Bellani, L., Ceolotto, S., Elsner, B., and Pestel, N. (2024). The effect of air pollution on voting behavior. *Proceedings of the National Academy of Sciences*, 121(18):e2309868121.

Burke, M., Driscoll, A., Heft-Neal, S., Xue, J., Burney, J., and Wara, M. (2022). Exposures and behavioural responses to wildfire smoke. *Nature Human Behaviour*, 6(10):1351–1361.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. C. (2024). Difference-in-differences with a continuous treatment. *NBER Working Paper*, (32117). arXiv:2107.02637.

Childs, M. L., Li, J. S., Wen, J., Heft-Neal, S., Drber, A., and Burke, M. (2022). Daily local-level estimates of ambient wildfire smoke PM2.5 for the contiguous US. *Environmental Science & Technology*, 56(19):13607–13621.

Gomez, B. T., Hansford, T. G., and Krause, G. A. (2007). Weather, turnout, and voting: Is weather a natural experiment? *The Journal of Politics*, 69(3):649–663.

Hazlett, C. and Mildenberger, M. (2020). Wildfire exposure increases pro-environment voting within Democratic but not Republican areas. *American Political Science Review*, 114(4):1359–1365.

Healy, A. and Malhotra, N. (2010). Myopic voters and natural disaster policy. *American Political Science Review*, 104(3):387–406.

Kahn, M. E. (2007). Voting for the environment: Environmental voters and environmental voting. *Journal of Public Economics*, 91(9):1609–1619.

MIT Election Data + Science Lab (2024). County presidential election returns 2000–2024. Harvard Dataverse.

Appendix

Table A1: Robustness: District-Level House Estimates

	(1) District House	(2) County House
Panel A: DEM Vote Share		
Mean Smoke PM$_{2.5}$ (60d)	−0.00027	0.00038***
	(0.00045)	(0.00013)
Panel B: Incumbent Vote Share		
Mean Smoke PM$_{2.5}$ (60d)	−0.00186**	−0.00153***
	(0.00089)	(0.00045)
Panel C: Log Total Votes		
Mean Smoke PM$_{2.5}$ (60d)	−0.00223	0.00177***
	(0.00150)	(0.00066)
Unit	District	County
FE	District + Year	County + Year
Observations	3,014 / 3,450	8,391 / 9,165
Elections	2006–2020	2016–2020

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. SEs clustered by unit.

District-level uses Census crosswalk to map county smoke to districts.