IGCC | UC INSTITUTE ON GLOBAL CONFLICT AND COOPERATION

WORKING PAPER NO. 14
SEPTEMBER 2023

Particulates Matter: Policy Failures, Air Pollution, and Collective Political Participation in the United States

Patrick Hunnicutt, Geoffrey Henderson

Abstract

Addressing policy failures such as crime, violence, and vulnerability to natural disasters often requires broad-based political participation. Prior research suggests policy failures themselves mobilize individuals to engage in politics, yet questions remain about how policy failures affect participation in the aggregate. While policy failures may make individuals more likely to participate, they also may undermine the collective action necessary to influence policy. We investigate the relationship between policy failures and aggregate-level political participation using the case of air pollution, a global threat to public well-being. Our research design leverages variation in particulate matter 2.5 dispersed by wind to estimate the effect of air pollution on county-level political participation in the United States. Our results show that air pollution undermines participation, likely because its health effects weaken individual and collective capacities for mobilization. Policy failures can be self-reinforcing—by undermining the prospects for mass mobilization, pollution may beget more pollution.

Keywords: pollution; policy failures; collection action; political participation; mobilization

This working paper was presented at the IGCC-sponsored Political Economy of Climate and the Environment (PECE) mini-conference, held at the UCLA Luskin Center on August 30, 2023.

Authors

Patrick Hunnicutt
Assistant Professor, Chapman University
Email: phunnicutt@chapman.edu

Geoffrey Henderson
Postdoctoral Associate, Duke University
Email: geoffrey.henderson@duke.edu

Acknowledgements

Thank you to EPW seminar participants at UCSB and attendees of the American Political Science Association 2022 and Midwest Political Science Association 2022 annual meetings for invaluable feedback.

Suggested Citation

Hunnicutt, Patrick and Geoffrey Henderson. 2023. *Particulates Matter: Policy Failures, Air Pollution, and Collective Political Participation in the United States*. IGCC Working Paper No 14. escholarship.org/uc/item/51h8846s

Introduction

Governments around the world frequently fail to provide public goods at an optimal level for society (Olson 1965), from security to environmental protection. Addressing such policy failures—or, the gap between the collective interest in a public good and the government's provision of it (McConnell 2015)—often requires broad-based political participation (Schreurs 2003; Leighley, and Oser 2018). Perhaps encouragingly, then, extant research shows that directly experiencing policy failures that impose significant personal harm can activate an individual to participate in politics (Blattman 2009; Bateson 2012; Garcia-Montoya, Arjona, and Lacombe 2022).

Yet questions remain about whether policy failures will result in greater political participation in the aggregate. While some research has shown policy failures to stimulate collective action, such as when police-caused deaths of Black people spark Black Lives Matter protests (Williamson, Trump, and Einstein 2018), other scholars caution against committing the individualistic fallacy. Policy failures may not mobilize the level of collective action required to address them, even if individuals who directly experience policy failures become more participatory. For instance, while crime victimization contributes to political participation, Bateson (2012) notes that communities with higher crime rates tend to also participate less. Do policy failures broaden or narrow political participation?

Our manuscript investigates this research question using the case of air pollution. Despite historic efforts to regulate air pollution, its negative effects on public well-being remain widespread. Ambient air pollution caused approximately 4.5 million premature deaths around the world in 2019, an alarming 55 percent increase from 2000 levels (Fuller et al. 2022). In 2014, the economic damages from air pollution cost the United States about 5 percent of its gross domestic product (Tschofen, Azevedo, and Muller 2019). Air pollution has also emerged as a public grievance, as organized groups increasingly interpret pollution as a social injustice (Bullard and Wright 2012). Notably, some governments in industrialized countries like the United States have recently relaxed existing policies regulating air pollution, gambling that the boost in extractive and industrial output will outweigh the sharp increases in costs to human health and labor productivity (Gamper-Rabindran 2022). In this sense, air pollution may be an increasingly ubiquitous form of policy failure.

People have collectively mobilized over the past century to curb air pollution, from London to Los Angeles to Lahore (Schreurs 2003; Presse 2021). The social movements and organizations that have formed to address environmental problems may suggest that air pollution in itself drives political participation (Johnson and Frickel 2011). However, participation is not always widespread in highly polluted places. For example, the American steel town of Gary, Indiana, experienced extraordinary levels of air pollution in the early postwar period, yet its residents did not demand policy regulating air pollution until much later (Crenson 1971).

The puzzling variation in collective action for air pollution abatement is consistent with competing theoretical predictions about pollution's mobilizing potential. Motivation-based theories suggest that air pollution may increase participation by engendering grievances and catalyzing individual- or group-level processes that facilitate collective action (Han 2009b; Blattman 2009; Bateson 2012; Williamson, Trump, and Einstein 2018). Yet resource-based theories suggest that air pollution may reduce participation by increasing its costs (Schloz- man, Brady, and Verba 2018), given its health effects. Empirically adjudicating between these predictions is difficult because air pollution correlates with other factors that influence participation, such as policies that discriminate on the basis of race, gender, or other identities (Bullard and Wright 2012; Pellow 2017; Trounstine 2020).

We use wind speed as an instrumental variable for cross-sectional variation in particulate matter 2.5 ($PM_{2.5}$) pollution across 414 counties in the American West—where highly granular estimates of $PM_{2.5}$ are available from 2008 through 2021 (Reid et al. 2021)—to estimate the effect of air pollution on political participation. We also use estimates of PM2.5 from van Donkelaar et al. (2021) to replicate our analyses across all counties in the contiguous United States. Our identification strategy builds from research evaluating air pollution's effects on economic productivity and health (Deryugina et al. 2019; He, Liu, and Salvo 2019; Kountouris 2020). We focus on $PM_{2.5}$ because it is ubiquitous and its abatement remains the focus of various organizations in the United States. Our measure of political participation leverages new data compiled by a prominent political action organization in the United States (hereafter, "Organization Z") that focuses on promoting climate action, economic reform, and social justice. These data document over 40,000 commitments to engage in various forms of activism, including participating in demonstrations and phone-banking for elected officials.

Our results suggest that air pollution reduces aggregate-level political participation. A 1 microgram per cubic meter increase in a county's average $PM_{2.5}$ exposure in 2018 reduces the number of commitments Organization Z members made in that county between 2019 and 2021 by 21. The negative relationship between air pollution and participation holds when we measure $PM_{2.5}$ levels as the number of days exceeding various air quality standards in 2018, use contemporaneous estimates of $PM_{2.5}$ pollution between 2019 and 2021, measure participation differently, and correct our standard errors for spatial autocorrelation. Our results also hold when we compile our standard errors using a non-parametric bootstrap (following Lal, Lockhart, and Zu (N.d.)), account for potential violations of the exclusion restriction such as storms, and exclude from our sample counties that experienced wildfires in 2018. We additionally find evidence of pollution's demobilizing potential when we use less temporally granular $PM_{2.5}$ estimates to include in our sample all counties in the contiguous United States.

Our findings appear to reflect air pollution's real and perceived health impacts. County- level $PM_{2.5}$ concentrations in 2018 correlate positively with chronic pulmonary obstructive diseases in 2019, and the negative relationship between $PM_{2.5}$ and participation is strongest in counties whose residents are more likely to perceive the short- and long-term risks of pollution exposure (Benney et al. 2021). Beyond its effect on individuals, we posit pollution may undermine aggregate participation as its health impacts erode the networks that mobilize participation.

Our study makes three contributions. First, we extend research on the relationship between policy failures, grievances, and political participation. Prior work shows that both the harms resulting from policy failures (Blattman 2009; Bateson 2012) and their corresponding grievances (Williamson, Trump, and Einstein 2018; Griffin, Jonge, and Velasco-Guachalla 2021) increase political participation. Qualitative differences between types of policy failures and their corresponding grievances may explain why we find that air pollution stifles participation while other failures stimulate it. Still, our findings align with the assertion that personal costs resulting from political processes directly affect participation (Han 2009a).

Second, our study bolsters limited research explaining aggregate-level political behavior (Gay 2004; Williamson, Trump, and Einstein 2018). Understanding what causes aggregate- level political participation matters because an individual's participation cannot be explained without understanding their position within their social context (Durkheim 1933; Granovetter 1978). Widespread participation is also more efficacious (Mayhew 1974; Henderson et al. 2021). Our findings align with prior suggestions that factors that stimulate individual-level participation may fail to increase group-level participation. This paradox may result from bystanders' free-riding (Bateson 2012), or indicate that air pollution's capacity to damage collective resources for mobilization exceeds its capacity to foment grievances.

Finally, we help bridge research on environmental justice and policy feedback (Soss 1999; Weaver and Lerman 2010). Our study begins to unearth a negative feedback loop between systemic discrimination, environmental problems, and political mobilization. Policies marginalizing groups based on race, gender, and other identities explain spatial and temporal variation in environmental problems (Bullard and Wright 2012; Pellow 2017), from air (Tessum et al. 2019) and water (Mueller and Gasteyer 2021) pollution to radioactive waste (Voyles 2015) and climate change (Harlan et al. 2015). Our results suggest that the same environmental problems these policies contribute to can go on to undermine broad-based political participation, which some argue is necessary to make systemic change (Chong 1987; Vogel 1993). By undermining the prospects for mass mobilization, pollution may bring about more pollution.

Theory

We present strong evidence that air pollution undermines collective political participation in the United States. But why might it be harder to mobilize broad-based political participation in more polluted places? We provide a conceptual response to this question, beginning by briefly clarifying why air pollution is a policy failure.

Air Pollution as a Policy Failure

What constitutes a policy failure remains an active debate among scholars of public policy and political science. More recent developments posit that government policies experience various degrees of failure that are either objective and subjective in nature (McConnell 2010, 2015). We specifically focus on the class of policy failures that reflect a gap between the collective interest in a public good and the government's provision of it, such as the U.S. government's failure to equitably provide assistance to communities affected by Hurricane Katrina (Han 2009b; Volcker 2014). Crime also falls within this class of policy failure, in that rising crime rates may signal either the failure of existing policies to promote security (one public good) or the government's failure to provide other public goods that contribute to crime reduction (e.g., healthcare or education) (Wen, Hockenberry, and Cummings 2017; Vogler 2020).

If policy failures stem from a gap between citizens' demands for public goods and the government's provision of them, then air pollution is clearly a policy failure. People around the world have long demanded from their governments stronger policies to regulate air pollution (Schreurs 2003) and mitigate its deleterious effects on human well-being (Fuller et al. 2022).[1] Yet over 90 percent of the world's population are

[1] Clean air is a public good because its consumption is both non-rivalrous and non-excludable.

exposed to air pollution levels exceeding World Health Organization guidelines, one-third of the world's countries lack any ambient air quality standards, and only one-third of countries with ambient air quality standards are legally obligated to meet them (UNEP 2021). Perhaps unsurprisingly, then, air pollution has worsened in many regions of the globe over the past two decades (Shaddick et al. 2020; Wolf et al. 2022; Sicard et al. 2023). Even in countries with robust national environmental policy frameworks, such as the United States, air pollution remains a problem for marginalized communities (Tessum et al. 2019) and in regions experiencing a combination of economic growth, reduced pollution enforcement, and increased wildfires (Clay, Muller, and Wang 2021).

Air Pollution and Political Participation

In many regions of the world, governments have failed to meet citizens' collective demand for cleaner air through effective pollution policies. To understand how such a policy failure might influence political participation, we distinguish between it as a lived experience and as a grievance. Living through government failures to curb air pollution may undermine political participation. Air pollution significantly threatens public health (Deryugina et al. 2019)—for instance, exacerbating chronic obstructive pulmonary diseases (Wu et al. 2019; Hsieh et al. 2021). Weather events that sharply increase air pollution, like wildfires (Liu et al. 2016) and temperature inversions (Gramsch et al. 2014), are public health hazards (Burke et al. 2021). Importantly, air pollution's effect on public health can materialize both on short (Williams et al. 2019) and long timescales (Lepeule et al. 2012). Moreover, certain air pollutants can harm human health even at concentrations lower than those current regulations deem acceptable (Dominici et al. 2022).

Air pollution's health risks may undermine aggregate political participation, for two reasons. First, its health impacts may reduce economic productivity and thereby increase the cost of collective action. Prolonged pollution exposure reduces days worked and worker output (Chang et al. 2019; He, Liu, and Salvo 2019; Kountouris 2020; Amoatey et al. 2021). When productivity declines, people have less time to participate in politics (Schlozman, Brady, and Verba 2018). If air pollution reduces the productivity of paid labor, it seems plausible that the voluntary labor, which civic engagement entails, will also suffer.

Second, even the threat of pollution exposure may deter participation. Air quality monitors and advisories are used worldwide to generate actionable information about pollution levels. Learning of increased pollution may affect people's evaluation of local air quality (Cori et al. 2020; Cobbold et al. 2022) contributing to anxiety, risk-averse behavior (Lerner and Keltner 2001), and a reduced appetite for civic engagement (Kam

2012; Brooks 2014).[2] Air pollution may also reduce political participation by depressing people's perceptions of external efficacy, or belief in their ability to influence government decisions. Strong perceptions of external efficacy strongly predict participation (Finkel 1985). Qualitative research on the experience of pollution has unearthed narratives stressing a loss of agency (Spencer- Hwang et al. 2014). Residents of Los Angeles who live near polluting infrastructures such as oil wells express how unabated exposure to pollution fosters feelings of powerlessness—they believe no political action can change their living conditions.[3]

Importantly, the timescales over which air pollution demobilizes political participation are likely more variable than those linking air pollution to health and economic outcomes. Extant research depicts political participation as both an individual's behavior and the product of a longer process reflecting the qualities of the individual's social network (Rosenstone and Hansen 1993; Verba, Schlozman, and Brady 1995; Han 2009b; Sinclair 2012; Green and Gerber 2019). This duality suggests air pollution could immediately deter participation by increasing avoidance behaviors, or reduce participation over time by exacerbating chronic illness. Meanwhile, pollution's effect on participation could compound over time within a social network. If pollution reduces participation among community leaders, these leaders in turn will be able to mobilize fewer additional participants, contributing to a vicious cycle of demobilization.

Altogether, air pollution's physical and psychological effects may increase the barriers to collective action, generating the following hypothesis:

H1: Air pollution reduces political participation.

By contrast, grievances resulting from failures to curb air pollution may catalyze political participation. Social scientists' stance on grievances' role in mobilization has oscillated widely (Griffin, Jonge, and Velasco-Guachalla 2021). As scholars began to identify factors that distinguished vibrant social movements from lost causes—including resource mobilization (McCarthy and Zald 1977), political opportunity (McAdam et al. 1999), and framing (Snow and Benford 1988)—grievances were increasingly depicted as an omnipresent scope condition with little explanatory power (Gurney and Tierney 1982) rather than an important cause of protest and revolution (Gurr 1970).

Still, foundational framing theorists Snow and Benford (1988) acknowledge that a collective action frame's capacity to mobilize increases when its audience can interpret

---

2 See Valentino et al. (2011) for an extensive discussion about the role of anxiety and risk-aversion in politics. Note that Levasseur et al. (2022) discusses the limitations of public pollution warnings as strategies to increase protective behaviors.

3 See 13:00 through 14:00 in *The Jefferson Drill*, produced by Stand Together Against Neighborhood Drilling, Los Angeles.

it as consistent with their lived experiences (i.e., grievances). Recent research substantiates this claim. People who experience the direct effects of policy successes recognize their stake in policy outcomes, gaining motivation to participate in future rounds of contention in those arenas (Campbell 2003). Likewise, those who experience the negative effects of a policy failure are driven to participate due to greater personal commitments to the cause (Han 2009b). Air pollution may spur participation through similar mechanisms—by allowing social movements to deploy more effective frames and by clarifying people's stakes in the policymaking process. Air pollution as a grievance may also directly mobilize individuals for politics. This effect may reflect post-traumatic growth, a desire to sublimate anger from experiencing harm, or engagement in social settings that foster feelings of efficacy among aggrieved individuals. For instance, Blattman (2009) shows that people forcibly enlisted as child soldiers in Ugandan rebel groups became more likely to participate in politics and even assume community leadership positions. Similarly, Bateson (2012) shows that crime victims are more likely to engage in various political activities. Even experts tend to approach political issues through the lens of their personal experiences with government and politics (Cramer and Toff 2017). Williamson, Trump, and Einstein (2018) extend this theory to the aggregate level, demonstrating that communities where police-caused deaths of Black people are more prevalent are more likely to protest such violence.

In addition to directly spurring mobilization, grievances can erode the government's legitimacy in the public's eyes. Indeed, Alkon and Wang (2018) find that experiencing air pollution erodes Chinese citizens' support for the local and central government. The resulting loss of faith in the government can spark protest, as De Juan and Wegner (2017) demonstrate in South Africa.

The environmental movement represents a bellwether for grievance theorists, as activism around environmental problems in industrialized democracies emerged only after pollution reached hazardous levels (Schreurs 2003). Since a grievance's tangibility moderates its influence, people are more likely to take action to address a problem that affects them directly and visibly (e.g., wildfire smoke) than a problem that appears temporally and spatially distant (e.g., climate change) (Ansolabehere and Konisky 2014). Indeed, Hart and Feldman (2021) find that messages focusing on emissions of local air pollutants from power plants inspire greater intent to participate in politics than similar messages stressing power plants' contribution to climate change.

Air pollution's capacity to activate existing grievances or foment new ones may mobilize people for collective action, generating the following hypothesis:

H2: Air pollution increases political participation.

The countervailing mechanisms underpinning H1 and H2 are not mutually exclusive. Air pollution can simultaneously raise the barriers to collective action and strengthen grievances that motivate people to engage in politics. Pollution's aggregate effect on participation likely reflects each mechanism's relative strength in a given setting. We anticipate that air pollution is more likely to demobilize people. Experiencing health effects may be necessary for pollution to activate or engender grievances. Yet not all people who experience pollution's effects become aggrieved (Crenson 1971).

Empirical Strategy

Measurement

We draw our evidence from an original cross-sectional dataset of $PM_{2.5}$ pollution, political participation, and climatic conditions across 414 counties in 11 states in the American West.[4] We focus on this sub-sample of American states due to the limited availability of daily, county-level estimates of $PM_{2.5}$ levels (Reid et al. 2021). We also extend our main analysis to all counties in the contiguous United States using less-granular estimates of $PM_{2.5}$ levels from van Donkelaar et al. (2021). We next describe the construction of this dataset.

Pollution

County-level estimates of surface-level $PM_{2.5}$ concentrations from 2008 to 2018 compiled by Reid et al. (2021) allow us to construct our measure of air pollution.[5] Our primary measure of air pollution is the average daily $PM_{2.5}$ concentration recorded per county in 2018 (Figure 1a). The greater temporal granularity these data offer also allow us to operationalize air pollution as the worst "air-day" recorded per county in 2018 and the number of days in excess of various air quality standards per county in 2018.[6]

4 The states in our sample are Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming.

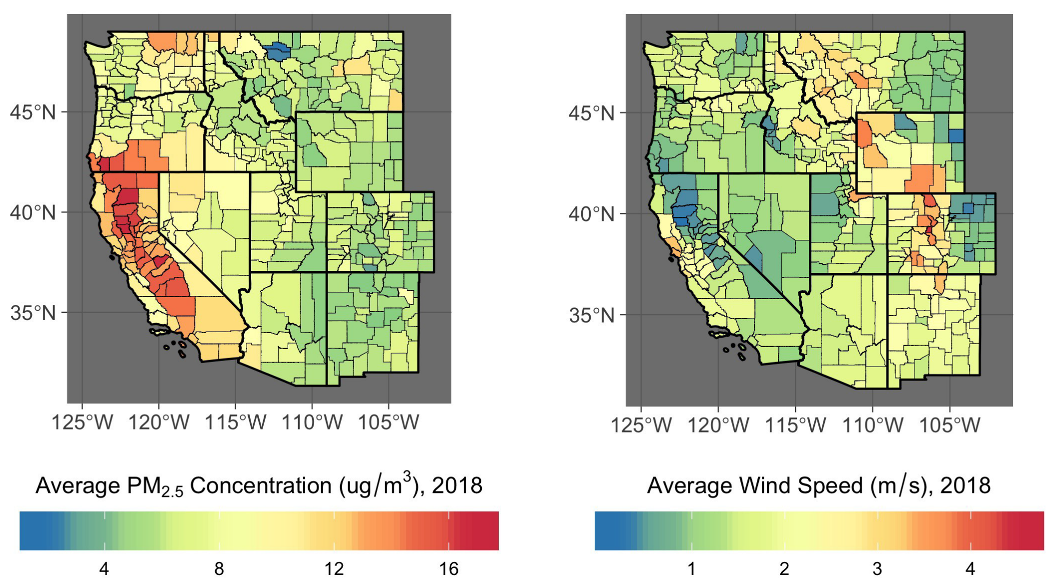
5 These $PM_{2.5}$ estimates are superior to those generated by combining basic spatial interpolation techniques like inverse distance weighting with pollution monitor data because they leverage satellite and pollution monitor data and employ more complex, machine learning-based methods of spatial interpolation. See Reid et al. (2021) for a more thorough discussion of these advantages.

6 In this section, we discuss why we opt for a cross-sectional approach over a longitudinal approach, whereby daily or monthly concentrations of $PM_{2.5}$ would be used to explain within-county variation in participation over time.

We choose to aggregate pollution data to the county level, as opposed to a smaller administrative unit, to minimize measurement error stemming from spillover in pollution exposure. For example, consider a county containing several Census tracts, each of which varies in its level of air pollution. It is likely that individuals within this county regularly travel to other Census tracts in the county (e.g., to commute for work), thereby exposing themselves to levels of air pollution that are different from those in their Census tract of residence. Compiling county-level measures of air pollution better accounts for these dynamics.

We focus on $PM_{2.5}$ because it is widespread, harmful, and seems relevant for political participation. $PM_{2.5}$ has a number of point sources (Childs et al. 2022; Jeong et al. 2019) and the U.S. Environmental Protection Agency is mandated to regulate $PM_{2.5}$ emissions. One recent study shows that $PM_{2.5}$ can cause excess deaths at levels that comply with current EPA regulations (Dominici et al. 2022). Abating $PM_{2.5}$ pollution has been the focus of various political actors and organizations in the United States. Indeed, the Sierra Club's "Beyond Coal" campaign points to the health effects of $PM_{2.5}$ as justification for phasing out coal-fired power plants (The Sierra Club 2023). Similarly, communities in Chicago's Southeast Side engaged in a 28-day demonstration to protest the nearby siting of a metal-scrapping facility that would expose residents to high levels of $PM_{2.5}$ pollution (Daley 2021).

Figure 1: Average County-Level PM2.5 Concentrations and Wind Speeds, 2018



(a) X: Air Pollution

(b) Z: Wind Speed

Wind Speed

We calculate each county's average wind speed in 2018 to construct an instrumental variable for county-level $PM_{2.5}$ exposure in 2018, using data from the National Oceanic and Atmospheric Administration (Figure 1b).[7] Wind speed affects the dispersion of air pollutants like $PM_{2.5}$ but is plausibly exogenous to other determinants of political participation. A more thorough discussion of this instrument and potential violations of the exclusion restriction is provided later.

Participation

We partner with a prominent political action organization in the United States ("Organization Z") to measure political participation. Organization Z is fairly new, having formed within the past decade. Among other proposed reforms, its current campaigns focus on achieving a just solution to climate change, creating well-paid jobs, and expanding access to affordable housing. Organization Z's membership skews younger, relative to other mass-based advocacy groups in the United States.

Our primary outcome measure is the count of actions that Organization Z members committed to taking per county between 2019 and 2021. Organization Z records when its members electronically commit to participate in forms of political advocacy it calls "highbar" actions—those that require a significant investment of time.[8] These actions include phone-banking for the organization's endorsed candidates, turning out for public demonstrations the organization coordinates, and taking part in the organization's various training activities. The population of commitments Organization Z recorded between the winter of 2019 and the fall of 2021—in total, 137,124 commitments from 56,177 of its members—allows us to measure our dependent variable. After receiving de-identified data from Organization Z, we aggregate them to the county level using records on members' zip codes.[9] Across the 414 counties in our final sample, approximately 17,000 different Organization Z members made over 40,000 commitments between 2019 and 2021 (Figure 2a).[10]

---

7 Accessed at https://psl.noaa.gov/repository/a/psdgrids, November 5, 2021.

8 While we refer to people who commit to participate in Organization Z's events as "members," people do not need to be a member of the organization to participate in its advocacy. Anyone may sign up to participate in Organization Z's events through links posted on social media.

9 Members' zip codes are matched to zip code tabulation area IDs from the U.S. Census Bureau, each of which correspond to a single county.

10 Of the 414 counties in our sample, 171 do not record any commitments between 2019 and 2021. Figure E1 visualizes the distribution of counties without any commitments recorded per state.

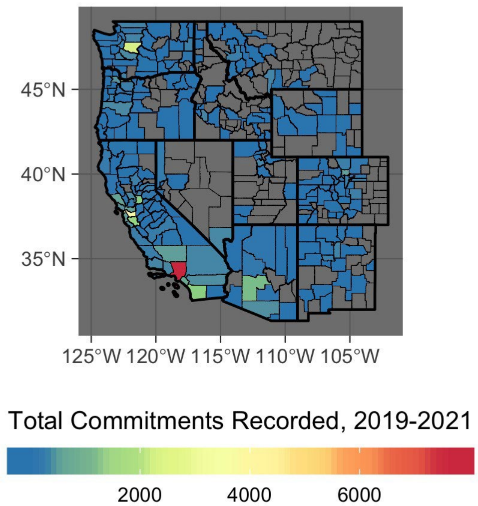
What is the distribution of commitments, both generally and across the different types of political participation Organization Z coordinates? We use the names of Organization Z events included in our data to categorize members' commitments into four groups: general meetings (e.g., participating in a Green New Deal watch party), training activities (e.g., preparation for a climate strike), canvassing (e.g., tabling on university campuses), and rallies (e.g., participating in a climate strike). We could not code 12,026 of the 133,159 total commitments to highbar actions in our data, due to the ambiguous naming of some events. Therefore, we encourage readers to interpret the following analyses as a loose categorization of Organization Z's activities.

Organization Z members in the contiguous United States registered approximately eight commitments on average between 2019 and 2021. More than 130 members made 50 commitments in the same time period, and 13 members made at least 100 commitments. Commitments to participate in Organization Z meetings are more prevalent in our data, followed by commitments to engage in training events. Members were most likely to attend a meeting as their first highbar action. The average number of commitments recorded by a member prior to committing to their first training activity, canvassing event, or rally were 2.51, 5, and 5.71, respectively.

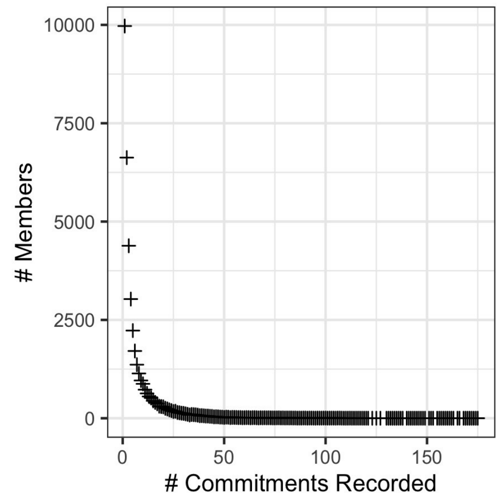
Members in our primary sample of 414 counties registered fewer commitments on average between 2019 and 2021 (2.4) compared to the average level of commitments recorded across the contiguous United States (Figure 2b). Still, the distribution of commitments per activity type (Figure 2c) and sequencing of commitments (Figure 2d) in our western sample of counties are largely consistent with that of all counties in the contiguous United States.

One advantage of our participation data is their focus on a broad array of political actions. While voting in an election is the most widespread and regular form of political participation, a great deal of public engagement in the democratic process occurs between elections. Compared to voting, "information-rich" forms of participation such as contacting elected officials are more likely to change representatives' perceptions of their constituents' desires regarding particular issues (Griffin and Newman 2005; Schlozman, Brady, and Verba 2018; Henderson et al. 2021).

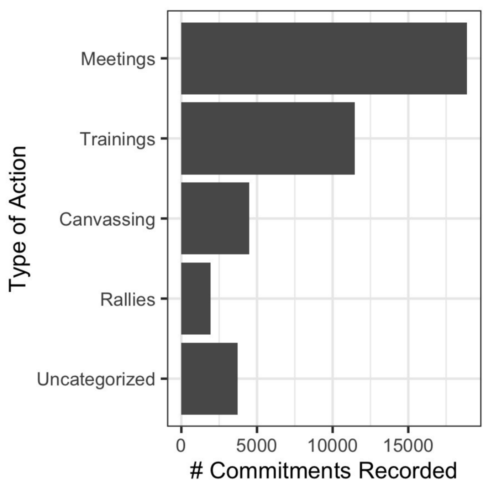
Figure 2: Commitments to Engage in Advocacy for Organization Z, 2019–2021



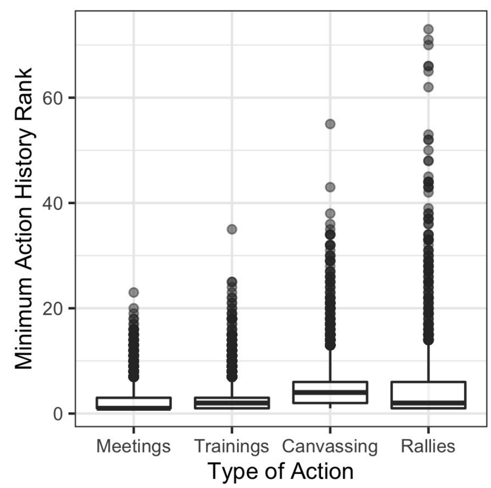
(a) Spatial Distribution of Commitments



(b) Commitments Recorded per Member



(c) Commitments by Activity Type



(d) Sequencing of Commitments

Note: Figure 2a visualizes the distribution of commitments recorded per county from 2019 through 2021. Warmer fills indicate counties with more commitments over the study period. Gray fills indicate counties where no commitments were recorded.

In addition to focusing on forms of political participation other than voting, our outcome measure attenuates concerns about response bias that characterize self-reported measures of participation (Bernstein, Chadha, and Montjoy 2001; Ansolabehere and Hersh 2012). Electronically registering for Organization Z activities online likely induces less social desirability bias than do ex-post surveys of participation. And while members' commitments may not perfectly match their attendance of Organization Z activities, research shows that making plans to engage in politics encourages subsequent participation (Nickerson and Rogers 2010). Nonetheless, we caution readers against treating our dependent variable as a perfectly validated measure of participation, despite its advantages over self-reports.

Identification & Estimation

Disentangling the relationship between air pollution and political participation is difficult. For one, any statistical analysis of air pollution and participation requires a modeling approach distinct from prior studies estimating air pollution's contemporaneous economic- and health-related effects. Political participation is the outcome of an ongoing social process in which people recruit each other to political activities (Rosenstone and Hansen 1993; Verba, Schlozman, and Brady 1995; Han 2009a; Sinclair 2012; Green and Gerber 2019). Because political participation is not completely atomized, the mechanisms through which it is affected by air pollution are more numerous and different—in terms of their spatial and temporal scales—than the mechanisms connecting air pollution to health and labor. All else equal, a large, short-term improvement in local air quality should quickly boost the productivity of individual workers by reducing absenteeism. The same improvement may not meaningfully change levels of political participation. Imagine that long-term exposure to air pollution undermined the health of a voluntary political organization's leadership, causing attrition in the organization's ranks over time. A short-run shift from high to low pollution levels would not immediately undo this harm to the organization's capacity for mobilization.

We therefore opt for a cross-sectional modeling approach that leverages county-level measures of participation between 2019 and 2021 and average daily $PM_{2.5}$ concentrations in 2018. Although our modeling approach will not precisely capture pollution's contemporaneous effects on participation, it should outperform a longitudinal approach in accounting for cumulative effects and avoiding unsubstantiated assumptions about functional form. For example, a longitudinal approach would require assumptions about the decay of air pollution's effects on participation, for which prior research offers little guidance. Still, we check if our results are robust to measuring air pollution as the average $PM_{2.5}$ concentration per county between 2019 and 2021.

Another challenge we face is accounting for the wide range of factors correlated with both $PM_{2.5}$ emissions and political participation. For example, industrial facilities both emit $PM_{2.5}$ and are the focus of grassroots mobilizing efforts (Temper et al. 2020). $PM_{2.5}$ emissions might also be concentrated in counties with particularly unresponsive elected officials or powerful economic interests (Crenson 1971)—both potential confounds. Moreover, existing research suggests pollution and politics are deeply endogenous. Scholars of environmental justice document how systemic barriers to political participation, based on race (Bullard and Wright 2012), gender (Voyles 2015), or a combination of identities (Pellow 2017), explain variation in pollution. Other work more specifically ties discriminatory lending and zoning practices to higher levels of (air) pollution in American cities (Taylor 2014; Lane et al. 2022). We employ an instrumental variable strategy to help address these two threats to identification, adapted from economics research on air pollution (e.g., Deryugina et al. 2019). A valid instrumental variable should be plausibly exogenous, correlated with the endogenous treatment of interest, and uncorrelated with other variables that explain the outcome of interest (i.e., satisfy the "exclusion restriction"). We describe how wind speed satisfies these criteria next.

A county's average wind speed should strongly predict its exposure to $PM_{2.5}$. Wind speed affects the horizontal transport of air pollutants like $PM_{2.5}$ (Li et al. 2017). Strong winds are more likely to disperse air pollution, so the correlation between average wind speed and average $PM_{2.5}$ concentration should be negative.

In order to satisfy the exclusion restriction, wind speed must be uncorrelated with other factors that influence aggregate levels of political participation. Our analysis addresses three potential violations of the exclusion restriction. First, we control for a county's urbanicity, because historic climatic conditions may be correlated with contemporary climatic conditions, urban development, and pollution. It is plausible that windier counties followed a unique development trajectory that both expose their residents to higher levels of air pollution and create a built environment that is more conducive to collective action. Second, we control for a county's average level of precipitation in 2018. This decision reflects how wind speed may simultaneously predict $PM_{2.5}$ concentrations and the onset of large storms, like hurricanes, which could deflate participation levels. Third, we adjust our estimation for the incidence of wildfires in 2018. Wildfires generate extraordinary levels of $PM_{2.5}$ (Burke et al. 2022) and are correlated with political participation (Hazlett and Mildenberger 2020).

To estimate the effect of $PM_{2.5}$ pollution on political participation, we employ a two-stage least squares (2SLS) regression where the first-stage is as follows:

$$PM_i = \alpha_i + \gamma_1 WindSpeed_i + \mathbf{X}_i + \mu_i \qquad (1)$$

We then leverage the fitted values of county-level $PM_{2.5}$ concentrations from Equation 1 to estimate our second-stage equation:

$$Y_i = \alpha_i + \gamma_1 \widehat{PM}_i + \mathbf{X}_i + \mu_i \qquad (2)$$

where *Y* is the total number of commitments registered in county *i* between 2019 and 2021 and μ_i are heteroskedasticity-consistent HC3 standard errors.[11] X_i includes a county's urbanicity, average precipitation in 2018, exposure to wildfires in 2018, and three other features of counties—derived from the 2016 American Community Survey—that should predict participation: income, population density, and population holding at least a bachelor's degree. Table D1 provides descriptive statistics for all variables used in our analysis.

Results

Table 1 reports the results of the first-stage relationship between wind speed and $PM_{2.5}$ in 2018. Wind speed negatively correlates with county-level $PM_{2.5}$ concentrations at the conventional level of statistical significance. The F-statistic of our first stage is approximately 48, surpassing the rule of thumb suggested in Stock, Wright, and Yogo (2002). Appendix B further the discusses the inferential strength of our results in light of concerns laid out in Lal, Lockhart, and Zu (N.d.).

Our second-stage results show that air pollution undermines political participation (model (a), Table 2). A 1 microgram per cubic meter increase in a county's average exposure to $PM_{2.5}$ in 2018 reduces the number of commitments Organization Z members registered between 2019 and 2021 by approximately 21. To help interpret this result, consider how it corresponds to plausible changes in a county's air pollution levels. Fremont County, Idaho experienced 5.89 micrograms per cubic meter of $PM_{2.5}$ on an average day in 2018, less than the average level of $PM_{2.5}$ recorded in 310 other counties in the same year. Our analysis suggests that increasing Fremont County's exposure to the mean concentration of $PM_{2.5}$ recorded across our sample of 414 western counties in 2018—7.926 micrograms per cubic meter—would undermine 42

[11] We opt to estimate a conventional 2SLS model, despite our count dependent variable, given outstanding concerns about computing correct standard errors (Newey 1987).

new commitments to engage in Organization Z's advocacy. Moving Fremont County's exposure across the interquartile range of $PM_{2.5}$ concentrations recorded in 2018—roughly, a 3 microgram per cubic meter increase—would prevent an additional 21 commitments. Given that the average number of commitments recorded among our sample of western counties between 2019 and 2021 is 4.2, we interpret this result as substantively significant.

Table 1: Wind Speed Strongly Predicts $PM_{2.5}$ Concentrations

	DV: Average $PM_{2.5}$ Concentration, 2018	
	(a)	(b)
Wind Speed	-1.285^{***}	-1.185^{***}
	(0.185)	(0.174)
Urban Population		0.022^{***}
		(0.004)
Population w/Bachelor's		0.000
		(0.000)
Population Density		1.540
		(1.500)
Median Income		−0.000
		(0.000)
Precipitation		0.181^{**}
		(0.088)
Fires		-1.144^{***}
		(0.434)
(Intercept)	10.096^{***}	8.971^{***}
	(0.372)	(0.686)
F-Statistic	48.050	21.110
Adj. R^2	0.113	0.223
Num. Obs.	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Using alternative measures of participation does not meaningfully change this result (Table D2). A 1 microgram per cubic meter increase in a county's average $PM_{2.5}$ concentration reduces the number of commitments recorded per 100,000 of its residents by 15.5, suggesting that air pollution limits both the absolute and relative extent of participation. Increasing a county's exposure to $PM_{2.5}$ also seems to reduce the probability that its residents registered any commitments to engage in Organization Z's activities, though this result is less precise. Moreover, relying on different measures of air pollution does not alter our core result (models (b–e), Table 2).

Table 2: Air Pollution Undermines Political Participation

	DV: Total Commitments, 2019–2021					
	(a)	(b)	(c)	(d)	(e)	(f)
Average $PM_{2.5}$ Concentration	-21.563^{**}					
	(9.262)					
Worst Air-Month		-7.432^{**}				
		(3.529)				
Worst Air-Day			-1.605^{**}			
			(0.781)			
Days w/AQI ≥ Unhealthy for Sens. Groups				-6.565^{**}		
				(3.001)		
Days w/AQI ≥ Unhealthy					-8.136^{**}	
					(3.714)	
Days w/AQI ≥ Very Unhealthy						-45.574^{*}
						(26.873)
Urban Population	−0.278	−0.824	−0.237	−0.130	−0.345	−0.460
	(0.525)	(0.533)	(0.557)	(0.578)	(0.526)	(0.535)
Population w/Bachelor's	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population Density	414.686	434.501	428.348	356.607	384.288	421.048
	(480.248)	(503.905)	(511.133)	(473.886)	(476.588)	(492.084)
Median Income	−0.002	−0.002	−0.001	−0.003	−0.002	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Precipitation	18.629^{**}	26.701^{***}	30.075^{***}	26.541^{***}	27.299^{***}	24.043^{***}
	(7.260)	(9.402)	(10.314)	(9.265)	(9.123)	(8.770)
Fires	−9.311	−6.170	−21.177	−26.831	−25.202	−24.507
	(27.051)	(25.114)	(31.577)	(31.531)	(28.566)	(27.232)
(Intercept)	166.707^{*}	182.686^{*}	102.419	93.636	49.278	41.911
	(94.955)	(106.540)	(86.427)	(83.804)	(76.229)	(77.101)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.05$
Wu-Hausman Test	$p < 0.05$	$p<0.05$	$p < 0.05$	$p < 0.01$	$p < 0.05$	$p < 0.05$
Adj. R^2	0.778	0.744	0.746	0.753	0.765	0.727
Num. Obs.	414	414	414	414	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Increasing the average concentration of $PM_{2.5}$ recorded during a county's poorest air-month in 2018 by 1 microgram per cubic meter reduces Organization Z members' subsequent commitments by seven. The same increase in the worst air-day recorded per county in 2018 reduces participation by two commitments, though this result falls just below the conventional level of statistical significance. Additional days in 2018 when the maximum $PM_{2.5}$ concentration recorded per county exceeded different tiers of the Environmental Protection Agency's Air Quality Index (AQI) also appear to reduce participation. For example, an additional day in exceedance of the AQI's "unhealthy" tier—indicating $PM_{2.5}$ levels are high enough to negatively affect the health of the entire population—reduces the number of commitments recorded between 2019 and 2021 by six. Our results also hold when we use different lags of $PM_{2.5}$ (Table D3), when we follow extant research on air pollution and economic productivity and measure contemporaneous $PM_{2.5}$ exposure (Table D4), and when we estimate spatial autocorrelation robust standard errors (Table D8).[12]

Unobservable characteristics of states, such as the timing of gubernatorial elections, may explain our results. We check whether this is the case by including state-level fixed effects in our 2SLS model. Doing so does not meaningfully change our results: The effect of $PM_{2.5}$ levels in 2018 on subsequent participation remains negative and statistically significant (Table D5). We additionally check whether our results are sensitive to excluding high-influence observations from our sample. We identify the following counties as high-influence observations by plotting their fitted values against their residuals (Figure E3): Multnomah County (Oregon), Maricopa County (Arizona), Los Angeles County (California), San Diego County (California), San Francisco County (California), Alameda County (California), and Orange County (California). Notably, some of these counties experienced a wildfire in 2018 (e.g., Alameda County). Removing these counties from our sample does not change our results (Table D6). We use monthly estimates of air pollution generated by van Donkelaar et al. (2021) to check whether our results replicate outside of the western United States. Doing so produces additional support for H1: A 1 microgram per cubic meter increase in the concentration of $PM_{2.5}$ recorded during an average air-month in 2018 reduces the number of commitments recorded per 100,000 residents by 19 and the probability of recording any commitments by 14 percentage points (Table D7). However, when relying on this larger sample, we fail to reject the null hypothesis that air pollution affects the total number of commitments recorded between 2019 and 2021.

Our estimator assumes a linear relationship between air pollution and political participation. Yet the relationship between pollution and participation may be non-linear. Low to moderate levels of air pollution may spur participation by signaling future government inaction on environmental problems, whereas high levels of air pollution may reduce participation by dramatically increasing its cost. The relationship may also be convex: Marginal increases in pollution from a low baseline may first reduce participation due to health effects but eventually increase participation as people's

[12] We operationalize contemporaneous air pollution by taking the average concentration of $PM_{2.5}$ recorded per county between 2019 and 2021 and then re-estimate our 2SLS model. To avoid inducing post-treatment bias, we do not recompile our covariate data so they correspond to counties' attributes in 2019–2021. Note that we can only estimate the relationship between contemporaneous air pollution and participation among the full sample of counties in the United States, using data from van Donkelaar et al. (2021), because Reid et al. (2021)'s estimates of $PM_{2.5}$ concentrations in western counties are not available after 2018.

grievances with the government crystallize. We investigate this potential non-linearity by including a quadratic measure of the average concentration of $PM_{2.5}$ in our primary specification, which we instrument using a quadratic measure of average wind speed.

We find mixed evidence of a convex relationship between air pollution and political participation. The relationship between the average county-level concentration of $PM_{2.5}$ in 2018 and subsequent commitments to participate in politics appears somewhat convex (Figure E4a), and we find marginal evidence of this relationship econometrically (model (a), Table D9). The effect of the quadratic measure of air pollution is positive and significant at the 10-percent level, while the effect of our original measure of air pollution is negative and significant. However, we suspect that Los Angeles County is driving this result. Excluding Los Angeles County from our sample both makes the descriptive relationship between pollution and participation appear more linear (Figure E4b) and renders our estimates statistically insignificant (model (b), Table D9).

Sources of Air Pollution

We take two steps to explore whether the source of air pollution influences its impact on political participation. First, we leverage new data on PM2.5 emissions from wildfires (Childs et al. 2022). Pollution from wildfires may be especially likely to influence participation because it is more "visible" than pollution from other primary sources (e.g., tailpipe emissions). However, whether air pollution from wildfire smoke increases or reduces participation is unclear. While Hazlett and Mildenberger (2020) find that proximity to a wildfire can subsequently increase voter turnout, Burke et al. (2022) show that people are more likely to stay home and seek information about air pollution and protective measures during large wildfire smoke events. Second, we use spatial data from the Environmental Protection Agency to split our sample into subgroups based on the local capacity of fossil fuel-fired power plants and then re-estimate the effect of $PM_{2.5}$ on participation. Like wildfire smoke, the presence of polluting infrastructures may increase public awareness of local air quality, but whether that increased awareness translates into more participation remains unclear.

Our analyses suggest that air pollution from wildfires could exert a stronger negative influence on participation than air pollution from other sources (Table D10), though the estimate of wildfire smoke's impact on participation is slightly imprecise. A 1 microgram per cubic meter increase in $PM_{2.5}$ pollution from wildfire smoke reduces the number of commitments recorded by Organization Z between 2019 and 2021 by approximately 31. This negative estimate persists, albeit imprecisely, when we narrow our focus to either commitments to engage in typically indoor organizing activities like trainings or commitments for typically outdoor activities like demonstrations.

We also find suggestive evidence that the presence of polluting infrastructures may amplify the demobilizing potential of $PM_{2.5}$. A 1 microgram per cubic meter increase in the average level of $PM_{2.5}$ pollution in 2018 reduces the number of commitments recorded between 2019 and 2021 by approximately 84 in counties with installed capacity to generate electricity from fossil fuels. In contrast, the same increase in pollution in a county with no installed fossil fuel generation capacity reduces the number of commitments by only about six (Table D11). However, these subgroup results are only statistically significant at the 10 percent level.

Mechanisms

Our results suggest that air pollution is more so a barrier to political participation than a catalyst for it. We now explore which of our proposed mechanisms underly this result. First, we use data from the Center for Disease Control on the county-level prevalence of chronic pulmonary obstructive disease (COPD) in 2019 to investigate whether the physical effects of air pollution explain the negative relationship between $PM_{2.5}$ and participation we estimate.

Second, we split our sample into subgroups along demographic and political features that may explain diverging beliefs about the risk of air pollution in the United States. Benney et al. (2021) find that liberal and wealthy Utahans are more likely than their peers to perceive air pollution as a short- and long-term risk to their health. If perceiving air pollution as a risk to human health increases avoidance behaviors that undermine collective action, we may observe a stronger negative relationship between $PM_{2.5}$ pollution and participation in wealthier and more liberal counties.

Finally, we test whether air pollution reduces political participation by eroding people's external efficacy. Two measures of external efficacy are available at the congressional district level from the 2020 wave of the American National Election Study.[13] Accordingly, we aggregate our data up to the congressional district level and test whether air pollution in 2018 is associated with perceptions of external efficacy in 2020.[14]

It seems plausible that air pollution reduces political participation because of its perceived and real impacts on human health. Average county-level concentrations of PM2.5 in 2016, 2017, and 2018 all positively correlate with the prevalence of COPD in 2019 (Table D12). We also find that the negative relationship between PM2.5 and

---

13 Appendix C discusses how we use these measures in our analyses.

14 We perform this test using our primary sample of 11 western states and in the larger sample of all states in the lower 48, given that there are only 99 congressional districts in the former.

participation is concentrated in counties that exceed the median vote share for the Democratic presidential candidate in 2016 elections (30.502 percent, Table D13). Higher levels of air pollution negatively correlate with participation among counties in our sample that exceed the in-sample median value of median household income ($24,520), though this result is only significant at the 10-percent level.

By comparison, we find little evidence suggesting air pollution reduces participation by making people feel less externally efficacious (Table D14). We fail to reject the null hypothesis that the average congressional-district-level concentration of $PM_{2.5}$ in 2018 is unrelated to external efficacy within our primary sample of 11 western states. Expanding this sample out to all congressional districts in the lower 48 states produces similarly uncertain results. Of course, these analyses have limitations. The null association between air pollution and external efficacy we estimate may be an artifact of insufficient statistical power, and county-level data on asthma-related hospitalizations and risk perceptions would facilitate more precise tests of our first two mechanisms. Nonetheless, we interpret these analyses as suggestive evidence that air pollution's capacity to threaten human health underpins its ability to reduce political participation.

Discussion & Conclusion

This paper provides, to our knowledge, the first systematic estimate of air pollution's effect on aggregate levels of political participation. Our results suggest that air pollution reduces participation, likely because air pollution's threat to public health raises the cost of collective action. They also call for a more systematic effort to understand how policy failures affect aggregate-level political participation.

For political participation scholars, it may seem puzzling that we find a stronger negative effect of $PM_{2.5}$ on participation in relatively wealthy, liberal counties. People in these counties should have more resources at their disposal to facilitate collective action and hold political beliefs that are consistent with mobilizing in response to environmental problems (McCarthy and Zald 1977). Threshold-based theories of participation stressing the importance of context may resolve this confusion. An individual's willingness to engage in collective action reflects their expectation of how many other members of their social context will mobilize, but people differ in terms of how many other people they need to see participating before they join in (Granovetter 1978; Margetts et al. 2015). Some will take up a cause they believe in even if it is not yet popular, while others will join once they see a critical mass of people engaging. Since high-resource communities have the means to bring unlikely participants off the sidelines, the marginal participant in a high-resource community may be especially susceptible to demobilization when the costs of participation increase.

We likely estimate a lower-bound of the magnitude of air pollution's demobilizing effect on political participation. We measure individuals' commitments to engage in modes of participation that extant research suggests to be more likely to elicit government reform (Wouters and Walgrave 2017). Individual decisions to mobilize for collective action partially reflect beliefs about the probability that said mobilization achieves government concessions. Therefore, it seems plausible that air pollution would be even more demobilizing in its relationship to less efficacious forms of political participation like voting.

Two scope conditions likely bound our theory and results. First, we suspect our findings reflect the specific intensity of air pollution in the United States. People's responses to air pollution may vary widely according to baseline air pollution levels. For example, counties in our sample were exposed to approximately 8 micrograms per cubic meter of $PM_{2.5}$ pollution on an average air-day in 2018. By contrast, the average concentration of $PM_{2.5}$ in the greater Delhi area was approximately 80 micrograms per cubic meter during the same year. An average air-day in Delhi may be so severe—relative to average levels of pollution in the United States— that it would expand political participation in the United States, similar to the effects of climate-related disasters (Hazlett and Mildenberger 2020; Koubi et al. 2021).

Second, our results may only hold in places where the average adult reports low levels of external efficacy. American citizens express low external efficacy relative to other countries in the Americas. Reductions in external efficacy can undermine collective action (Finkel 1985). All else equal, then, poor air quality may be insufficient to deter participation in settings where people are more confident that their voices will spur government action.

Future research might expand upon three elements of our study. First, disaggregating $PM_{2.5}$ emissions by their sources could yield additional insights. Air pollution from certain sources (e.g., coal-fired power plants) may be especially likely to mobilize participation because the resulting emissions are directly attributable to an actor the government is tasked with regulating. Air pollution that is easier to attribute to government action may help crystallize people's political grievances. Second, theorizing more carefully around the impact of air pollution on different kinds of participation could prove fruitful. Air pollution may be more likely to dissuade people from less information-rich and efficacious forms of participation like voting, as we have suggested. Finally, future research could investigate the relationship between air pollution and participation on different timescales using longitudinal data. For example, it seems plausible that people would be more willing to engage in collective action immediately after experiencing abnormally high levels of air pollution than they would after experiencing several years of poor air quality and its related impacts on public health. As we suggest above, answering such a question would require researchers to both generate novel data and make principled assumptions about the functional form of the pollution-participation relationship.

In conclusion, this study makes three contributions. First, we extend the limited body of political science research explaining aggregate-level participation, shedding light on factors that an individual-level analysis would overlook. Second, our analyses generate new insights for the debate about the relationship between policy failures, grievances, and political participation. Finally, our results help bridge existing research on environmental justice and negative policy feedback loops. Policy failures can be self-reinforcing—by undermining the prospects for mass mobilization, pollution may beget more pollution.

References

Alkon, Meir and Erik H. Wang. 2018. "Pollution lowers support for China's regime: Quasi- experimental evidence from Beijing." *The Journal of Politics* 80(1):327–331.

Amoatey, Patrick, Hamid Omidvarborna, Mahad Said Baawain, Issa Al-Harthy, Abdullah Al-Mamun, and Khalifa Al-Jabri. 2021. "Preliminary hazard assessment of air pollution levels in Nizwa, Rusayl and Sur in Oman." *Journal of Environmental Engineering and Science* 40:1–9.

Ansolabehere, Stephen and David M. Konisky. 2014. *Cheap and clean: how Americans think about energy in the age of global warming*. MIT Press.

Ansolabehere, Stephen and Eitan Hersh. 2012. "Validation: What big data reveal about survey misreporting and the real electorate." *Political Analysis* 20(4):437–459.

Bateson, Regina. 2012. "Crime Victimization and Political Participation." *American Political Science Review* 106(3):570—587.

Benney, Tabitha M, Devon Cantwell, Phillip Singer, Linda Derhak, Samuel Bey, and Zahra Saifee. 2021. "Understanding Perceptions of Health Risk and Behavioral Responses to Air Pollution in the State of Utah (USA)." *Atmosphere* 12(11):1373.

Bernstein, Robert, Anita Chadha, and Robert Montjoy. 2001. "Overreporting voting: Why it happens and why it matters." *Public Opinion Quarterly* 65(1):22–44.

Blattman, Christopher. 2009. “From violence to voting: War and political participation in Uganda.” *American political Science Review* 103(2):231–247.

Brooks, Sarah M. 2014. “Insecure democracy: Risk and political participation in Brazil.” *The Journal of Politics* 76(4):972–985.

Bullard, Robert D. and Beverly Wright. 2012. *The wrong complexion for protection.* New York University Press.

Burke, Marshall, Anne Driscoll, Sam Heft-Neal, Jiani Xue, Jennifer Burney, and Michael Wara. 2021. “The changing risk and burden of wildfire in the United States.” *Proceedings of the National Academy of Sciences* 118(2):e2011048118.

Burke, Marshall, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick Baylis, Matthieu Stigler, Joakim A. Weill, Jennifer A. Burney, Jeff Wen, Marissa L. Childs, et al. 2022. “Exposures and behavioural responses to wildfire smoke.” *Nature: Human Behaviour* pp. 1–11.

Campbell, Tim. 2003. *The quiet revolution: Decentralization and the rise of political participation in Latin American cities.* University of Pittsburgh Press.

Cassell, Kaitlen J. 2021. “Representation in the Americas: Perceptions of External Efficacy in the 2018/19 AmericasBarometer.” https://www.vanderbilt.edu/lapop/insights/IO946en.pdf.

Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2019. “The effect of pollution on worker productivity: evidence from call center workers in China.” *American Economic Journal: Applied Economics* 11(1):151–72.

Childs, Marissa L., Jessica Li, Jeffrey Wen, Sam Heft-Neal, Anne Driscoll, Sherrie Wang, Carlos F. Gould, Minghao Qiu, Jennifer Burney, and Marshall Burke. 2022. “Daily Local-Level Estimates of Ambient Wildfire Smoke PM2.5 for the Contiguous US.” *Environmental Science & Technology*. PMID: 36134580.

Chong, Dennis. 1987. *Collective action and the civil rights movement.* University of Chicago Press.

Clay, Karen, Nicholas Z. Muller and Xiao Wang. 2021. “Recent increases in air pollution: evidence and implications for mortality.” *Review of Environmental Economics and Policy* 15(1):154–162.

Cobbold, Alec T., Melanie A. Crane, Luke D. Knibbs, Ivan C. Hanigan, Stephen P. Greaves, and Chris E. Rissel. 2022. "Perceptions of air quality and concern for health in relation to long-term air pollution exposure, bushfires, and COVID-19 lockdown: A before-and-after study." *The Journal of Climate Change and Health* p. 100137.

Cori, Liliana, Gabriele Donzelli, Francesca Gorini, Fabrizio Bianchi and Olivia Curzio. 2020. "Risk perception of air pollution: A systematic review focused on particulate matter exposure." *International Journal of Environmental Research and Public Health* 17(17):6424.

Cramer, Katherine J. and Benjamin Toff. 2017. "The fact of experience: Rethinking political knowledge and civic competence." *Perspectives on Politics* 15(3):754–770.

Crenson, Matthew A. 1971. *The Un-Politics of Air Pollution: A Study of Non-Decisionmaking in the Cities.* The Johns Hopkins Press.Daley, Jim. 2021. "Hunger Strikers Seeking Environmental Justice Win Air-Pollution Delay." *Scientific American.*

De Juan, Alexander and Eva Wegner. 2017. "Social inequality, state-centered grievances, and protest: Evidence from South Africa." *Journal of Conflict Resolution* 63(1):31–58.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. 2019. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review* 109(12):4178–4219.

Dominici, Francesca, Antonella Zanobetti, Joel Schwartz, Danielle Braun, Ben Sabath, and Xiao Wu. 2022. "Assessing Adverse Health Effects of Long-Term Exposure to Low Levels of Ambient Air Pollution: Implementation of Causal Inference Methods." *Research Report (Health Effects Institute)* (211):1–56.

Durkheim, Emile. 1933. "The division of labor in society (G. Simpson, Trans.)." *New York: The Free Press.*

Finkel, Steven E. 1985. "Reciprocal effects of participation and political efficacy: A panel analysis." *American Journal of Political Science* pp. 891–913.

Fuller, Richard, Philip J. Landrigan, Kalpana Balakrishnan, Glynda Bathan, Stephan Bose-O'Reilly, Michael Brauer, Jack Caravanos, Tom Chiles, Aaron Cohen, Lilian Corra, et al. 2022. "Pollution and health: a progress update." *The Lancet Planetary Health.*

Gamper-Rabindran, Shanti. 2022. *America's energy gamble: people, economy, and planet.* Cambridge University Press.

Garcia-Montoya, Laura, Ana Arjona, and Matthew Lacombe. 2022. “Violence and voting in the United States: How school shootings affect elections.” *American Political Science Review* 116(3):807–826.

Gay, Claudine. 2004. “Putting race in context: identifying the environmental determinants of black racial attitudes.” *American political Science Review* 98(4):547–562.

Gramsch, E., D. Cáceres, P. Oyola, F. Reyes, Y. Vásquez, M. A. Rubio, and G. Sánchez. 2014. “Influence of surface and subsidence thermal inversion on PM2. 5 and black carbon concentration.” *Atmospheric Environment* 98:290–298.

Granovetter, Mark. 1978. “Threshold models of collective behavior.” *American Journal of Sociology* 83(6):1420–1443.

Green, Donald P. and Alan S. Gerber. 2019. *Get Out the Vote: How to Increase Voter Turnout.* Brookings Institution Press.

Griffin, John D. and Brian Newman. 2005. “Are voters better represented?” *The Journal of Politics* 67(4):1206–1227.

Griffin, John D., Chad Kiewiet De Jonge, and Vania Ximena Velasco-Guachalla. 2021. “Deprivation in the Midst of Plenty: Citizen Polarization and Political Protest.” *British Journal of Political Science* 51:1080–1096.

Gurney, Joan Neff and Kathleen J. Tierney. 1982. “Relative deprivation and social movements: A critical look at twenty years of theory and research.” *The Sociological Quarterly* 23(1):33– 47.

Gurr, Ted Robert. 1970. *Why Men Rebel.* Routledge.

Han, Hahrie. 2009a. *Moved to Action: Motivation, Participation, and Inequality in American Politics.* Stanford University Press.

Han, Hahrie C. 2009b. “Does the content of political appeals matter in motivating participation? A field experiment on self-disclosure in political appeals.” *Political Behavior* 31(1):103–116.

Harlan, Sharon L., David N Pellow, J. Timmons Roberts, Shannon Elizabeth Bell, William G. Holt, and Joane Nagel. 2015. “Climate justice and inequality.” *Climate Change and Society: Sociological Perspectives* pp. 127–163.

Hart, P. Sol and Lauren Feldman. 2021. “The benefit of focusing on air pollution instead of climate change: how discussing power plant emissions in the context of air pollution, rather than climate change, influences perceived benefits, costs, and political action for policies to limit emissions.” *Science Communication* 43(2):199–224.

Hazlett, Chad and Matto Mildenberger. 2020. “Wildfire exposure increases pro-environment voting within democratic but not republican areas.” *American Political Science Review* 114(4):1359–1365.

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. “Severe air pollution and labor productivity: Evidence from industrial towns in China.” *American Economic Journal: Applied Economics* 11(1):173–201.

Henderson, Geoffrey, Alexander Hertel-Fernandez, Matto Mildenberger, and Leah C. Stokes. 2021. “Conducting the Heavenly Chorus: Constituent Contact and Provoked Petitioning in Congress.” *Perspectives on Politics* pp. 1–18.

Hsieh, Shizuka, Elgloria Harrison, Janet A. Phoenix, and Rhonda Hamilton. 2021. “Asthma and particulate matter pollution: Insights from health survey and air quality monitoring in the Buzzard Point, Washington, DC neighborhood.” *Environmental Justice* 14(4):254–266.

Jeong, Cheol-Heon, Jon M. Wang, Nathan Hilker, Jerzy Debosz, Uwayemi Sofowote, Yushan Su, Michael Noble, Robert M. Healy, Tony Munoz, Ewa Dabek-Zlotorzynska, et al. 2019. “Temporal and spatial variability of traffic-related PM2. 5 sources: Comparison of exhaust and non-exhaust emissions.” *Atmospheric Environment* 198:55–69.

Joe, Adam. 2015. *The Jefferson Drill Documentary.* Redeemer Community Partnership.

Johnson, Erik W. and Scott Frickel. 2011. “Ecological Threat and the Founding of U.S. National Environmental Movement Organizations, 1962-1998.” *Social Problems* 58(3):305—329.

Kam, Cindy D. 2012. “Risk attitudes and political participation.” *American Journal of Political Science* 56(4):817–836.

Koubi, Vally, Quynh Nguyen, Gabriele Spilker, and Tobias Böhmelt. 2021. “Environmental migrants and social-movement participation*.” Journal of Peace Research* 58(1):18–32.

Kountouris, Yiannis. 2020. “Ambient PM2. 5 influences productive activities in public sector bureaucracies.” *Environmental Research Communications* 2(4):041003.

Lal, Apoorva, Mac Lockhart, and Yiqing Xu Stanford Ziwen Zu. N.d. "How Much Should We Trust Instrumental Variable Estimates in Political Science? Practical Advice based on 57 Replicated Studies." https://apoorvalal.github.io/files/papers/LLXZIV.pdf.

Lane, Haley M., Rachel Morello-Frosch, Julian D. Marshall, and Joshua S. Apte. 2022. "Historical Redlining Is Associated with Present-Day Air Pollution Disparities in US Cities." *Environmental Science & Technology Letters.*

Leighley, Jan E. and Jennifer Oser. 2018. "Representation in an Era of Political and Economic Inequality: How and When Citizen Engagement Matters." *Perspectives on Politics* 16(2):328–344.

Lepeule, Johanna, Francine Laden, Douglas Dockery, and Joel Schwartz. 2012. "Chronic exposure to fine particles and mortality: an extended follow-up of the Harvard Six Cities study from 1974 to 2009." *Environmental Health Perspectives* 120(7):965–970.

Lerner, Jennifer S. and Dacher Keltner. 2001. "Fear, anger, and risk." *Journal of Personality and Social Psychology* 81(1):146.

Levasseur, Pierre, Katrin Erdlenbruch, Christelle Gramaglia, Sofia Bento, Lúcia Fernandes, and Pedro Baños Páez. 2022. "Does pollution perception lead to risk avoidance behaviour? A mixed methods analysis." *Review of Social Economy* pp. 1–27.

Li, Xiaolan, Yanjun Ma, Yangfeng Wang, Ningwei Liu, and Ye Hong. 2017. "Temporal and spatial analyses of particulate matter (PM10 and PM2. 5) and its relationship with meteorological parameters over an urban city in northeast China." *Atmospheric Research* 198:185–193.

Liu, Jia Coco, Loretta J. Mickley, Melissa P. Sulprizio, Francesca Dominici, Xu Yue, Keita Ebisu, Georgiana Brooke Anderson, Rafi FA Khan, Mercedes A. Bravo, and Michelle L. Bell. 2016. "Particulate air pollution from wildfires in the Western US under climate change." *Climatic Change* 138(3):655–666.

Margetts, Helen, Peter John, Scott Hale, and Taha Yasseri. 2015. *Political turbulence: How social media shape collective action.* Princeton University Press.

Mayhew, David R. 1974. "Congressional elections: The case of the vanishing marginals." *Polity* 6(3):295–317.

McAdam, Doug, et al. 1999. *Political process and the development of black insurgency, 19301970.* University of Chicago Press.

McCarthy, John D. and Mayer N. Zald. 1977. “Resource mobilization and social movements: A partial theory.” *American Journal of Sociology* 82(6):1212–1241.

McConnell, Allan. 2010. “Policy success, policy failure and grey areas in-between.” *Journal of Public Policy* 30(3):345–362.

McConnell, Allan. 2015. “What is policy failure? A primer to help navigate the maze.” *Public Policy and Administration* 30(3-4):221–242.

Mueller, J. Tom and Stephen Gasteyer. 2021. “The widespread and unjust drinking water and clean water crisis in the United States.” *Nature Communications* 12(1):1–8.

Newey, Whitney K. 1987. “Efficient estimation of limited dependent variable models with endogenous explanatory variables.” *Journal of Econometrics* 36(3):231–250.

Nickerson, David W. and Todd Rogers. 2010. “Do you have a voting plan? Implementation intentions, voter turnout, and organic plan making.” *Psychological Science* 21(2):194–199.

OECD. 2020. Exposure to PM2.5 in countries and regions. Technical report, Organisation for Economic Co-operation and Development. https://stats.oecd.org/Index.aspx?DataSetCode=EXPP M 25.

Olson, Mancur. 1965. *The logic of collective action.* Harvard University Press.

Pellow, David Naguib. 2017. *What is critical environmental justice?* John Wiley & Sons.

Presse, Agence France. 2021. “Pakistan: ‘Find a solution,’ say Lahore residents choking in smog.” https://www.aljazeera.com/news/2021/11/17/pakistan-lahore-smog-air-pollution- aqi-health.

Reid, Colleen E., Ellen M. Considine, Melissa M. Maestas, and Gina Li. 2021. “Daily PM2. 5 concentration estimates by county, ZIP code, and census tract in 11 western states 2008–2018.” *Scientific Data* 8(1):1–15.

Rosenstone, Steven J. and John Mark Hansen. 1993. *Mobilization, Participation, and Democracy in America.* Macmillan Publishing Company.
Schlozman, Kay Lehman, Henry E. Brady, and Sidney Verba. 2018. *Unequal and Unrepresented.* Princeton University Press.

Schreurs, Miranda A. 2003. *Environmental Politics in Japan, Germany, and the United States*. Cambridge University Press.

Shaddick, Gavin, Matthew L. Thomas, Pierpaolo Mudu, Giulia Ruggeri, and Sophie Gumy. 2020. “Half the world’s population are exposed to increasing air pollution.” *NPJ Climate and Atmospheric Science* 3(1):23.

Sicard, Pierre, Evgenios Agathokleous, Susan C. Anenberg, Alessandra De Marco, Elena Paoletti, and Vicent Calatayud. 2023. “Trends in urban air pollution over the last two decades: A global perspective.” *Science of The Total Environment* 858:160064.

Sinclair, Betsy. 2012. *The Social Citizen: Peer Networks and Political Behavior*. The University of Chicago Press.

Snow, David A. and Robert D. Benford. 1988. Master Frames and Cycles of Protest. *In Frontiers in Social Movement Theory*, ed. Aldon D. Morris and Carol McClurg Mueller. New Haven: Yale University Press chapter 6, pp. 133–155.

Soss, Joe. 1999. “Lessons of welfare: Policy design, political learning, and political action.” *American Political Science Review* 93(2):363–380.

Spencer-Hwang, Rhonda, Susanne Montgomery, Molly Dougherty, Johanny Valladares, Sany Rangel, Peter Gleason, and Sam Soret. 2014. “Experiences of a rail yard community: Life is hard.” *Journal of Environmental Health* 77(2):8.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo. 2002. “A survey of weak instruments and weak identification in generalized method of moments.” *Journal of Business & Economic Statistics* 20(4):518–529.

Taylor, Dorceta. 2014. *Toxic communities.* New York University Press.

Temper, Leah, Sofia Avila, Daniela Del Bene, Jennifer Gobby, Nicolas Kosoy, Philippe Le Billon, Joan Martinez-Alier, Patricia Perkins, Brototi Roy, Arnim Scheidel, et al. 2020. “Movements shaping climate futures: A systematic mapping of protests against fossil fuel and low-carbon energy projects.” *Environmental Research Letters* 15(12):123004.

Tessum, Christopher W., Joshua S. Apte, Andrew L. Goodkind, Nicholas Z. Muller, Kimberley A. Mullins, David A. Paolella, Stephen Polasky, Nathaniel P. Springer, Sumil K. Thakrar, Julian D. Marshall, et al. 2019. “Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure.” *Proceedings of the National Academy of Sciences* 116(13):6001–6006.

The Sierra Club. 2023. “We’re Moving Beyond Coal and Gas.” https://coal.sierraclub.org/campaign.

Trounstine, Jessica. 2020. "The geography of inequality: How land use regulation produces segregation." *American Political Science Review* 114(2):443–455.

Tschofen, Peter, Inês L. Azevedo, and Nicholas Z. Muller. 2019. "Fine particulate matter damages and value added in the US economy." *Proceedings of the National Academy of Sciences* 116(40):19857–19862.

UNEP. 2021. "Regulating Air Quality the First Global Assessment of Air Pollution Legislation."

Valentino, Nicholas A., Ted Brader, Eric W. Groenendyk, Krysha Gregorowicz, and Vincent L. Hutchings. 2011. "Election night's alright for fighting: The role of emotions in political participation." *The Journal of Politics* 73(1):156–170.

van Donkelaar, Aaron, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, et al. 2021. "Monthly global estimates of fine particulate matter and their uncertainty." *Environmental Science & Technology* 55(22):15287–15300.

Verba, Sidney, Kay Lehman Schlozman, and Henry E. Brady. 1995. *Voice and equality: Civic voluntarism in American politics*. Harvard University Press.

Vogel, David. 1993. *Representing Diffuse Interests in Environmental Policymaking. In Do Institutions Matter?* Government Capabilities in the United States and Abroad., ed. R. Kent Weaver and Bert A. Rockman. The Brookings Institution pp. 237–271.

Vogler, Jacob. 2020. "Access to healthcare and criminal behavior: Evidence from the ACA Medicaid expansions." *Journal of Policy Analysis and Management* 39(4): 1166–1213.

Volcker, Paul A. 2014. "Vision without execution is hallucination." *Public Administration Review* pp. 439–441.

Voyles, Traci Brynne. 2015. *Wastelanding: Legacies of uranium mining in Navajo country.* University of Minnesota Press.

Weaver, Vesla M. and Amy E. Lerman. 2010. "Political consequences of the carceral state."*American Political Science Review* 104(4):817–833.

Wen, Hefei, Jason M. Hockenberry, and Janet R. Cummings. 2017. "The effect of Medicaid expansion on crime reduction: Evidence from HIFA-waiver expansions." *Journal of Public Economics* 154:67–94.

Williams, Austin M., Daniel J. Phaneuf, Meredith A. Barrett, and Jason G. Su. 2019. “Short- term impact of PM2. 5 on contemporaneous asthma medication use: Behavior and the value of pollution reductions.” *Proceedings of the National Academy of Sciences* 116(12):5246–5253.

Williamson, Vanessa, Kris-Stella Trump, and Katherine Levine Einstein. 2018. “Black lives matter: Evidence that police-caused deaths predict protest activity.” *Perspectives on Politics* 16(2):400–415.

Wolf, Martin J., Daniel C. Esty, Honghyok Kim, Michelle L. Bell, Sam Brigham, Quinn Norton- Smith, Slaveya Zaharieva, Zachary A. Wendling, Alex de Sherbinin, and John W. Emerson. 2022. “New insights for tracking global and local trends in exposure to air pollutants.” *Environmental Science & Technology* 56(7):3984–3996.

Wouters, Ruud and Stefaan Walgrave. 2017. “Demonstrating Power: How Protest Persuades Political Representatives.” *American Sociological Review* 82(2):361–383.

Wu, Jinzhun, Taoling Zhong, Yu Zhu, Dandan Ge, Xiaoliang Lin, and Qiyuan Li. 2019. “Effects of particulate matter (PM) on childhood asthma exacerbation and control in Xiamen, China.” *BMC Pediatrics* 19(1):1–11.

Appendices

"Particulates Matter: Policy Failures, Air Pollution, and Collective Political Participation in the United States."

Contents

Appendix A: Compliance with Principles and Guidance for Human Subjects Research

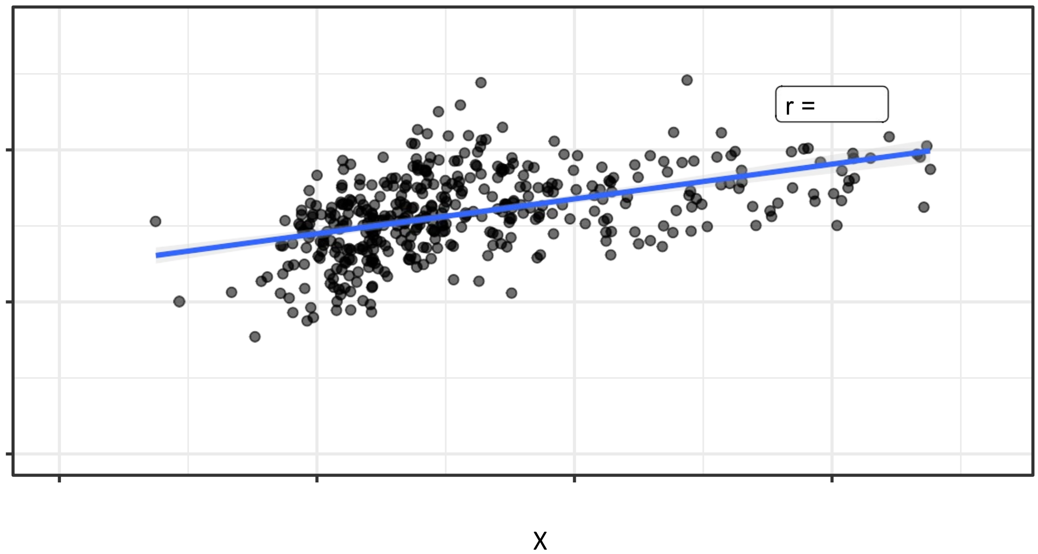
All research activities were deemed exempt from human subjects review by an institutional review board at a university in the United States (protocol number: 22-21-0599). Importantly, though, the researchers and their activities never engaged with human subjects because the research only involved the analysis of observational data Organization Z already collects. Additional evidence of this statement:

- The researchers did not initiate any new data collection efforts by Organization Z, nor did they alter Organization Z's existing data collection efforts.
- The researchers never gained access to the identifiable data Organization Z collects.
- No research activities involved deception because the research team never interacted with the members of Organization Z.
- No research activities intervened in political processes because the research team never interacted with the members of Organization Z.
- The researchers' use of Organization Z's data falls within the use-agreement it maintains with its members, which includes the following statement about voluntary and informed consent: “"[Organization] uses Users' personal information to better understand how Users use the Website so that it can improve the Website and [organization's] offerings. In addition, [organization] uses Users' personal information for the purpose for which the Users provided the information for example, to add you to our mailing list, to contact you about forming a new [organization group], or to register you for an event, or to process a donation. If you provide [organization] with your email address, you will be added to [organization's] email list and you will start receiving email communications from [organization], unless you opt out. If at any time you wish to stop receiving email communications from [organization], please follow the unsubscribe instructions at the bottom of any email [organization] sends you, or send [organization] an email at [organization email] and ask to be removed from [organization's] email list. If you provide [organization] with your phone number, you consent to receiving phone calls and text messages from [organization]. If you wish to be removed from [organization's] phone list, reply STOP to any text message from [organization], or email [organization email] and ask to be removed from [organization's] phone list.” According to Organization Z, this language implies that the organization does not explicitly guarantee its members that their deidentified data will not be shared with external partners for the purpose of research.

Thus, we believe the described research activities are in compliance with the American Political Science Association's principles and guidance for human subjects research.

Appendix B:Diagnosing Inferential Strength of 2SLS

Figure B1: Observed vs. Fitted Values of County-Level PM2.5 Concentration in 2018



We diagnose the inferential strength of our 2SLS estimates in three ways, following the guidelines laid out in Lal, Lockhart, and Zu (N.d.). First, we plot the observed and fitted values of county-level air pollution in 2018 to visually inspect the strength of our instrument. Figure B1 confirms our first-stage results. Our observed and fitted values of counties' average exposure to $PM_{2.5}$ in 2018 are positive correlated (r = 0.486).

Second, we estimate the first-stage F-statistic after calculating our standard errors using a non-parametric bootstrap. This procedure generates a value of 45.1944, which is negligibly smaller than the first-stage F-statistic we estimate using robust standard errors (46.3673). Thus, we are confident that our instrument is not weak.

Third, we use a non-parametric bootstrap to re-estimate the standard errors and confidence intervals of our 2SLS results. Although this procedure yields a slightly larger standard error than that displayed in Table 2, the substantive and statistical significance of our core result does not change the substantive or statistical significance of our results (est. = −21.563, std. error = 9.3376, 95-percent CI: [−43.36, −5.81], p-val. = 0.0026). Therefore, we remain confident in our core result.

Appendix C: Measuring External Efficacy from the American National Election Survey

We focus on questions V202212 and V202213. The first question asks respondents to state their level of agreement with the following statement: “Public officials don’t care much what people like me think.” The second question asks respondents to state their level of agreement with the following statement: “People like me don’t have any say about what the government does.” Responses were recorded on a 5-point Likert scale, ranging from strongly agree (1) to strongly disagree (5). We first take the mean response per congressional district. Then, we form two binary variables indicating whether the average respondent in a congressional district reported to strongly or somewhat disagree with the aforementioned statements.

Appendix D: Additional Tables

Table D1: Summary Statistics

	No. Observations	Mean	Std. Dev.	Min	Max	Range
Total Commitments, 2019–2021	414.00	97.45	488.17	0.00	7663.00	7663.00
Commitments per 100000 Residents, 2019–2021	414.00	28.43	65.90	0.00	905.80	905.80
Any Commitments Recorded, 2019-2021 (0/1)	414.00	0.58	0.49	0.00	1.00	1.00
Average $PM_{2.5}$ Concentration, 2018 ($\mu g/m^3$)	414.00	7.93	2.89	1.87	16.91	15.04
Average $PM_{2.5}$ Concentration, 2017 ($\mu g/m^3$)	414.00	7.65	2.78	1.52	15.87	14.36
Average $PM_{2.5}$ Concentration, 2016 ($\mu g/m^3$)	414.00	6.02	2.28	-0.22	17.07	17.29
Average $PM_{2.5}$ Concentration of Worst Air-Month, 2018 ($\mu g/m^3$)	414.00	22.93	12.88	6.43	79.73	73.30
Maximum $PM_{2.5}$ Concentration, 2018 ($\mu g/m^3$)	414.00	0.24	0.43	0.00	1.00	1.00
Days Exceeding Unhealthy for Sens. Groups AQI, 2018	414.00	12.57	14.00	0.00	71.00	71.00
Days Exceeding Unhealthy AQI, 2018	414.00	5.61	9.44	0.00	55.00	55.00
Days Exceeding Very Unhealthy AQI, 2018	414.00	0.60	2.71	0.00	30.00	30.00
Days Exceeding Hazardous AQI, 2018	414.00	0.07	0.57	0.00	8.00	8.00
Wind Speed, 2018 (m/s)	414.00	1.69	0.76	0.20	4.55	4.35
Wind Speed, 2017 (m/s)	414.00	1.62	0.77	0.15	4.43	4.28
Wind Speed, 2016 (m/s)	414.00	1.67	0.72	0.18	4.30	4.11
Population Density (population/km^2)	414.00	0.05	0.16	0.00	1.65	1.65
Percent of Population in Urban Areas	414.00	48.81	33.69	0.00	100.00	100.00
Population with Bachelor's Degree	414.00	23197.06	89183.84	43.00	1348250.00	1348207.00
Median Household Income (USD)	414.00	25708.36	5762.50	10201.00	60166.00	49965.00
Average Monthly Precipitation, 2018 (in.)	414.00	1.79	1.35	0.17	9.24	9.06
100+ Acre Fires Occurred in 2018 (0/1)	414.00	0.01	0.10	0.00	1.00	1.00
Democratic Vote Share, 2016 (percent of total vote)	414.00	0.33	0.17	0.05	0.85	0.80

Table D2: Second-Stage Results, Alternative Measure of Participation

	DV: Total Commitments per 100k Residents, 2019–2021	DV: Any Commitments Recorded (0/1), 2019–2021
	(a)	(b)
Average $PM_{2.5}$ Concentration	-16.982^{***}	-0.045^{*}
	(6.232)	(0.025)
Urban Population	0.437^{***}	0.008^{***}
	(0.144)	(0.001)
Population w/Bachelor's	0.000	0.000
	(0.000)	(0.000)
Population Density	106.823^{*}	0.166
	(55.870)	(0.112)
Median Income	0.001	−0.000
	(0.001)	(0.000)
Precipitation	11.147^{***}	0.089^{***}
	(3.000)	(0.014)
Fires	-26.656^{***}	−0.112
	(9.858)	(0.138)
(Intercept)	90.027^{*}	0.429^{*}
	(48.654)	(0.224)
Weak Instruments Test	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.01$	$p < 0.01$
Adj. R^2	−0.368	0.199
Num. Obs.	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D3: Second-Stage Results, Alternative Measure of Participation

	DV: Total Commitments, 2019–2021	
	(a)	(b)
Average $PM_{2.5}$ Concentration, 2017	-20.449^{**}	
	(9.915)	
Average $PM_{2.5}$ Concentration, 2016		-19.193^{**}
		(8.750)
Urban Population	−0.373	−0.367
	(0.469)	(0.458)
Population w/Bachelor's	0.005^{***}	0.005^{***}
	(0.001)	(0.001)
Population Density	393.060	385.078
	(461.467)	(454.188)
Median Income	−0.003	−0.002
	(0.003)	(0.003)
Precipitation	20.750^{***}	13.020^{*}
	(6.974)	(6.788)
Fires	10.911	1.713
	(28.271)	(22.685)
(Intercept)	177.590	123.085
	(115.194)	(95.765)
Weak Instruments Test	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p > 0.1$	$p < 0.1$
Adj. R^2	0.783	0.792
Num. Obs.	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D4: Second-Stage Results, Contemporaneous Pollution

	DV: Total Commitments, 2019–2021	DV: Total Commitments per 100k Residents, 2019–2021	DV: Any Commitments Recorded (0/1), 2019–2021
	(a)	(b)	(c)
Average $PM_{2.5}$ Concentration, 2019–2021	-21.446^{*}	-28.643^{***}	-0.261^{***}
	(12.105)	(6.334)	(0.043)
Urban Population	-0.599^{**}	0.324^{***}	0.008^{***}
	(0.279)	(0.062)	(0.000)
Population w/Bachelor's	0.005^{***}	0.000^{***}	0.000^{***}
	(0.001)	(0.000)	(0.000)
Population Density	81.812^{**}	7.761^{***}	-0.038^{***}
	(32.286)	(2.931)	(0.014)
Median Income	-0.002^{*}	0.001^{***}	0.000^{***}
	(0.001)	(0.000)	(0.000)
Precipitation	0.728	6.386^{***}	0.097^{***}
	(3.318)	(1.441)	(0.012)
Fires	−6.851	-15.180^{***}	-0.153^{***}
	(5.118)	(2.449)	(0.034)
(Intercept)	192.252^{***}	146.560^{***}	1.191^{***}
	(64.478)	(36.723)	(0.251)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p > 0.1$	$p < 0.01$	$p < 0.01$
Adj. R^2	0.692	−0.188	0.006
Num. Obs.	3108	3108	3108

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D5: Second-Stage Results, State Fixed Effects

	DV: Total Commitments, 2019–2021	DV: Total Commitments per 100k Residents, 2019–2021	DV: Any Commitments Recorded (0/1), 2019–2021
	(a)	(b)	(c)
Average $PM_{2.5}$ Concentration, 2018	-51.234^{**}	-36.129^{***}	-0.115^{**}
	(23.200)	(12.662)	(0.053)
Urban Population	−0.276	0.403^{***}	0.008^{***}
	(0.518)	(0.154)	(0.001)
Population w/Bachelor's	0.005^{***}	−0.000	−0.000
	(0.001)	(0.000)	(0.000)
Population Density	387.140	84.843^{**}	0.051
	(465.195)	(36.264)	(0.115)
Median Income	−0.002	0.000	−0.000
	(0.003)	(0.001)	(0.000)
Precipitation	−3.389	−1.664	0.021
	(12.524)	(4.177)	(0.022)
Fires	8.244	−5.421	0.080
	(39.966)	(25.919)	(0.154)
(Intercept)	276.370	215.041^{**}	1.032^{***}
	(176.648)	(91.295)	(0.398)
State Fixed Effects?	Yes	Yes	Yes
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.05$	$p < 0.01$	$p < 0.01$
Adj. R^2	0.765	−0.609	0.213
Num. Obs.	414	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D6: Second-Stage Results, Excluding High Influence Observations

	DV: Total Commitments, 2019–2021
	(a)
Average $PM_{2.5}$ Concentration, 2018	-11.764^{***}
	(4.390)
Urban Population	-0.076
	(0.233)
Population w/Bachelor's	0.004^{***}
	(0.001)
Population Density	97.525
	(112.661)
Median Income	-0.001
	(0.001)
Precipitation	11.815^{**}
	(4.755)
Fires	-10.656
	(18.105)
(Intercept)	77.718^{**}
	(36.704)
Weak Instruments Test	$p < 0.01$
Wu-Hausman Test	$p < 0.01$
Adj. R^2	0.773
Num. Obs.	407

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D7: Second-Stage Results, Including All Counties in Contiguous United States

	DV: Total Commitments, 2019–2021	DV: Total Commitments per 100k Residents, 2019–2021	DV: Any Commitments Recorded (0/1), 2019–2021
	(a)	(b)	(c)
Average $PM_{2.5}$ Concentration, 2018	−10.118	-19.053^{***}	-0.142^{***}
	(8.744)	(4.293)	(0.023)
Urban Population	-0.666^{**}	0.267^{***}	0.008^{***}
	(0.269)	(0.053)	(0.000)
Population w/Bachelor's	0.005^{***}	0.000^{***}	0.000^{***}
	(0.001)	(0.000)	(0.000)
Population Density	81.043^{**}	10.457^{***}	−0.017
	(31.734)	(3.546)	(0.013)
Median Income	-0.002^{*}	0.001^{***}	0.000^{***}
	(0.001)	(0.000)	(0.000)
Precipitation	0.765	8.824^{***}	0.106^{***}
	(4.469)	(1.917)	(0.011)
Fires	−1.551	-7.804^{***}	-0.084^{***}
	(3.483)	(1.605)	(0.030)
(Intercept)	108.690^{***}	58.854^{***}	0.254^{**}
	(34.325)	(18.004)	(0.108)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p > 0.1$	$p < 0.01$	$p < 0.01$
Adj. R^2	0.697	−0.018	0.191
Num. Obs.	3105	3105	3105

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D8: Second-Stage Results, Spatial Autocorrelation Robust Std. Errors

	DV: Total Commitments, 2019–2021
	(a)
Average $PM_{2.5}$ Concentration, 2018	-20.81^{***}
	(5.45)
Urban Population	-0.28^{***}
	(0.05)
Population w/Bachelor's	0.00^{***}
	(0.00)
Population Density	402.86^{***}
	(115.72)
Median Income	-0.00^{***}
	(0.00)
Precipitation	17.98^{***}
	(4.38)
Fires	-10.02^{*}
	(4.67)
(Intercept)	162.99^{***}
	(35.05)
Weak Instruments Test	$p < 0.01$
Wu-Hausman Test	$p < 0.05$
Adj. R^2	0.78
Num. Obs.	414

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D9: Second–Stage Results, Varying Functional Form

	DV: Total Commitments, 2019–2021				DV: Total Commitments per 100k Residents, 2019–2021	
	(a)	(b)	(c)	(d)	(e)	(f)
Average $PM_{2.5}$ Concentration	-102.907^{**}	-54.548			-108.089^{**}	-109.171^{**}
	(46.810)	(38.295)			(47.672)	(48.113)
Average $PM_{2.5}$ Concentration^2	4.549^{*}	1.809			5.095^{**}	5.157^{**}
	(2.517)	(1.951)			(2.386)	(2.411)
Days w/AQI ≥ Unhealthy			-89.363^{**}	-64.191		
			(45.353)	(41.309)		
Days w/AQI ≥ Unhealthy^2			3.277^{*}	2.111		
			(1.796)	(1.586)		
Urban Population	-0.140	0.395	-0.599	-0.043	0.591^{***}	0.579^{***}
	(0.487)	(0.412)	(0.563)	(0.495)	(0.184)	(0.183)
Population w/Bachelor's	0.005^{***}	0.003^{***}	0.005^{***}	0.003^{***}	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Population Density	397.413	678.019	568.884	779.664	87.477^{**}	81.200^{**}
	(470.518)	(429.531)	(582.177)	(532.916)	(38.707)	(37.681)
Median Income	-0.001	0.001	-0.001	0.001	0.002^{**}	0.002^{**}
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Precipitation	19.015^{***}	21.149^{***}	49.510^{**}	43.709^{**}	11.579^{***}	11.532^{***}
	(7.133)	(8.167)	(19.783)	(17.619)	(3.115)	(3.119)
Fires	18.720	-21.277	-38.746	-55.966	4.738	5.633
	(38.443)	(34.698)	(63.312)	(37.041)	(17.688)	(17.900)
(Intercept)	451.041^{**}	206.398	49.834	-21.963	408.486^{**}	413.959^{**}
	(219.961)	(185.574)	(88.875)	(84.932)	(189.659)	(191.929)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.05$	$p < 0.1$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Excluded Los Angeles County?	No	Yes	No	Yes	No	Yes
Adj. R^2	0.782	0.577	0.631	0.354	-0.558	-0.569
Num. Obs.	414	413	414	413	414	413

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D10: Second–Stage Results, Wildfire Smoke

	DV: Total Commitments, 2019–2021	DV: Total Commitments for Organizing, 2019–2021	DV: Total Commitments for Mobilizing, 2019–2021
	(a)	(b)	(c)
Average $PM_{2.5}$ from Wildfire Smoke	-30.907^{*}	-19.366^{*}	-5.227^{*}
	(16.757)	(10.882)	(2.804)
Urban Population	−0.795	−0.413	-0.183^{*}
	(0.559)	(0.331)	(0.109)
Population w/Bachelor's	0.005^{***}	0.003^{***}	0.001^{***}
	(0.001)	(0.001)	(0.000)
Population Density	490.563	322.887	51.011
	(542.876)	(332.740)	(92.081)
Median Income	0.001	0.001	0.000
	(0.003)	(0.002)	(0.001)
Precipitation	37.853^{**}	24.649^{**}	5.882^{**}
	(14.942)	(9.772)	(2.481)
Fires	24.605	11.400	8.005
	(47.872)	(29.538)	(8.787)
(Intercept)	130.201	73.565	24.929
	(101.176)	(62.922)	(17.996)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.01$	$p < 0.1$	$p < 0.01$
Adj. R^2	0.700	0.685	0.644
Num. Obs.	414	414	414

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D11: Second–Stage Results, Installed Capacity Subgroups

	Installed Capacity from Fossil Fuels = 0	Installed Capacity from Fossil Fuels > 0
	(a)	(b)
Average $PM_{2.5}$ from Wildfire Smoke	-6.441^{*}	-84.482^{*}
	(3.703)	(50.575)
Urban Population	−0.275	1.715
	(0.322)	(2.706)
Population w/Bachelor's	0.005^{*}	0.005^{***}
	(0.003)	(0.001)
Population Density	562.443	497.323
	(942.438)	(602.251)
Median Income	−0.003	−0.001
	(0.003)	(0.007)
Precipitation	2.457	42.326^{**}
	(4.592)	(18.393)
Fires	3.345	−101.545
	(15.977)	(114.825)
(Intercept)	110.739	481.247
	(80.929)	(298.080)
Weak Instruments Test	$p < 0.05$	$p < 0.01$
Wu-Hausman Test	$p < 0.05$	$p < 0.5$
Adj. R^2	0.631	0.679
Num. Obs.	268	146

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D12: Mechanisms: Prevalence of Chronic Pulmonary Obstructive Disease (COPD), 2019

	DV: Prevalence of COPD (% of population), 2019		
	(a)	(b)	(c)
Average $PM_{2.5}$ Concentration, 2018	0.218^{***}		
	(0.056)		
Average $PM_{2.5}$ Concentration, 2017		0.243^{***}	
		(0.054)	
Average $PM_{2.5}$ Concentration, 2016			0.250^{***}
			(0.059)
Urban Population	-0.010^{***}	-0.009^{***}	-0.010^{***}
	(0.002)	(0.002)	(0.002)
Population w/Bachelor's	-0.000^{**}	-0.000^{**}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
Population Density	-1.165^{**}	-1.103^{***}	-1.032^{***}
	(0.473)	(0.412)	(0.357)
Median Income	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
Precipitation	−0.041	-0.081^{**}	0.011
	(0.030)	(0.036)	(0.025)
Fires	0.407	0.172	0.277
	(0.312)	(0.369)	(0.298)
(Intercept)	6.933^{***}	6.540^{***}	7.059^{***}
	(0.566)	(0.587)	(0.517)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.01$	$p < 0.05$	$p < 0.05$
Adj. R^2	0.156	0.230	0.185
Num. Obs.	413	413	413

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D13: Mechanisms: Demographic and Political Subgroups

	Median Income: High	Median Income: Low	Democratic Vote Share: High	Democratic Vote Share: Low
	(a)	(b)	(c)	(d)
Average $PM_{2.5}$ Concentration, 2018	-50.518^{*}	-1.454	-40.163^{**}	0.607
	(26.582)	(1.795)	(16.945)	(0.463)
Urban Population	-0.355	0.039	0.083	0.019
	(1.003)	(0.140)	(0.986)	(0.015)
Median Income			-0.003	-0.000
			(0.004)	(0.000)
Population w/Bachelor's	0.005^{***}	0.005^{**}	0.005^{***}	0.000
	(0.001)	(0.002)	(0.001)	(0.000)
Population Density	488.205	-745.838	466.424	100.337^{*}
	(507.896)	(492.372)	(509.861)	(54.750)
Precipitation	21.778^{*}	3.993	24.740^{**}	1.402^{**}
	(13.002)	(2.571)	(9.647)	(0.665)
Fires	19.442	1.714	-43.345	-0.610
	(53.878)	(1.691)	(57.928)	(0.957)
(Intercept)	321.099^{*}	1.517	309.190^{*}	-4.740
	(182.491)	(13.263)	(174.885)	(3.802)
Weak Instruments Test	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Wu-Hausman Test	$p < 0.05$	$p > 0.1$	$p < 0.01$	$p > 0.1$
Adj. R^2	0.746	0.416	0.745	0.359
Num. Obs.	207	207	207	207

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

Table D14: Mechanisms: External Efficacy

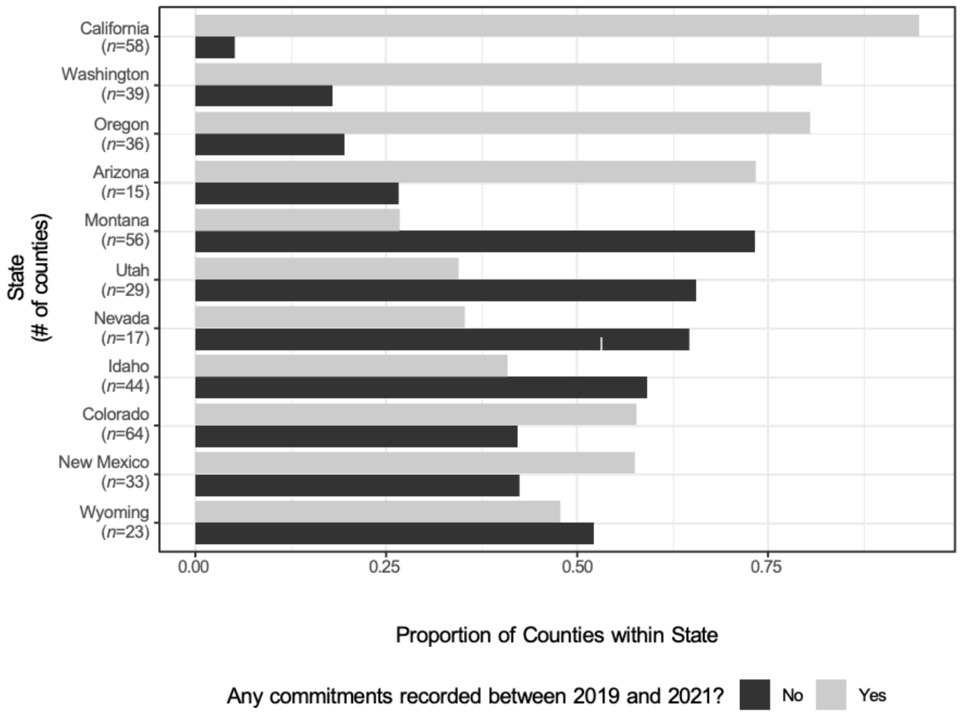
	Have no say in the government (0/1)		Gov't officials don't care about me (0/1)	
	(a)	(b)	(c)	(d)
Average $PM_{2.5}$ Concentration, 2018	−0.066	0.052	−0.016	0.024
	(0.155)	(0.047)	(0.055)	(0.031)
Urban Population	0.006	0.001	0.002	0.000
	(0.009)	(0.002)	(0.004)	(0.001)
Population w/Bachelor's	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Population Density	0.093	-0.015^{*}	−0.024	−0.006
	(0.641)	(0.008)	(0.202)	(0.004)
Median Income	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.012	0.013	−0.016	−0.007
	(0.026)	(0.012)	(0.010)	(0.008)
Fires	1.184	-0.187^{***}	−0.337	-0.063^{**}
	(2.763)	(0.069)	(1.315)	(0.031)
(Intercept)	0.638	−0.351	0.033	−0.153
	(1.769)	(0.278)	(0.636)	(0.173)
Weak Instruments Test	$p > 0.1$	$p < 0.01$	$p > 0.1$	$p < 0.01$
Wu-Hausman Test	$p > 0.1$	$p > 0.1$	$p > 0.1$	$p > 0.1$
Adj. R^2	−0.395	−0.042	−0.086	−0.042
Num. Obs.	97	426	97	426

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Heteroskedasticity-consistent HC3 standard errors are displayed in parentheses.

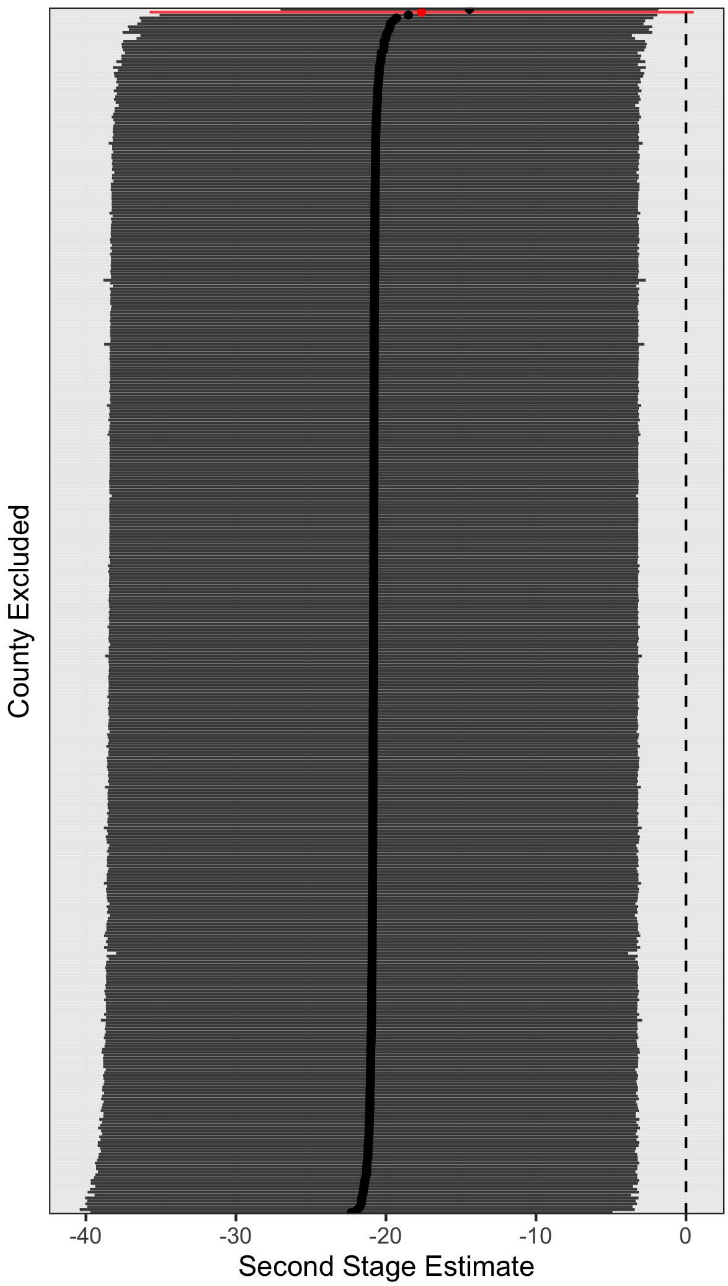
Appendix E: Additional Figures

Figure E1: Distribution of Counties with/without Commitments Recorded between 2019 and 2021



Note: This figure visualizes the proportion of counties per state in which at least one commitment to engage in a highbar action was (not) recorded between 2019 and 2021. States are ordered vertically based on the absolute difference between the proportion of counties with and without at least one commitment recorded.

Figure E2: Leave-1-Out Analysis



Note: Each point represents the estimated effect of the average county-level concentration of PM2.5 in 2018 on commitments to engage in Organization Z's advocacy between 2019 and 2021 after having excluded one county from our sample. Ninety-five percent confidence intervals are displayed. The red point and confidence interval correspond to the estimated impact of air pollution on participation when San Francisco, CA is excluded from our sample.

Figure E3: Potential High Influence Observations

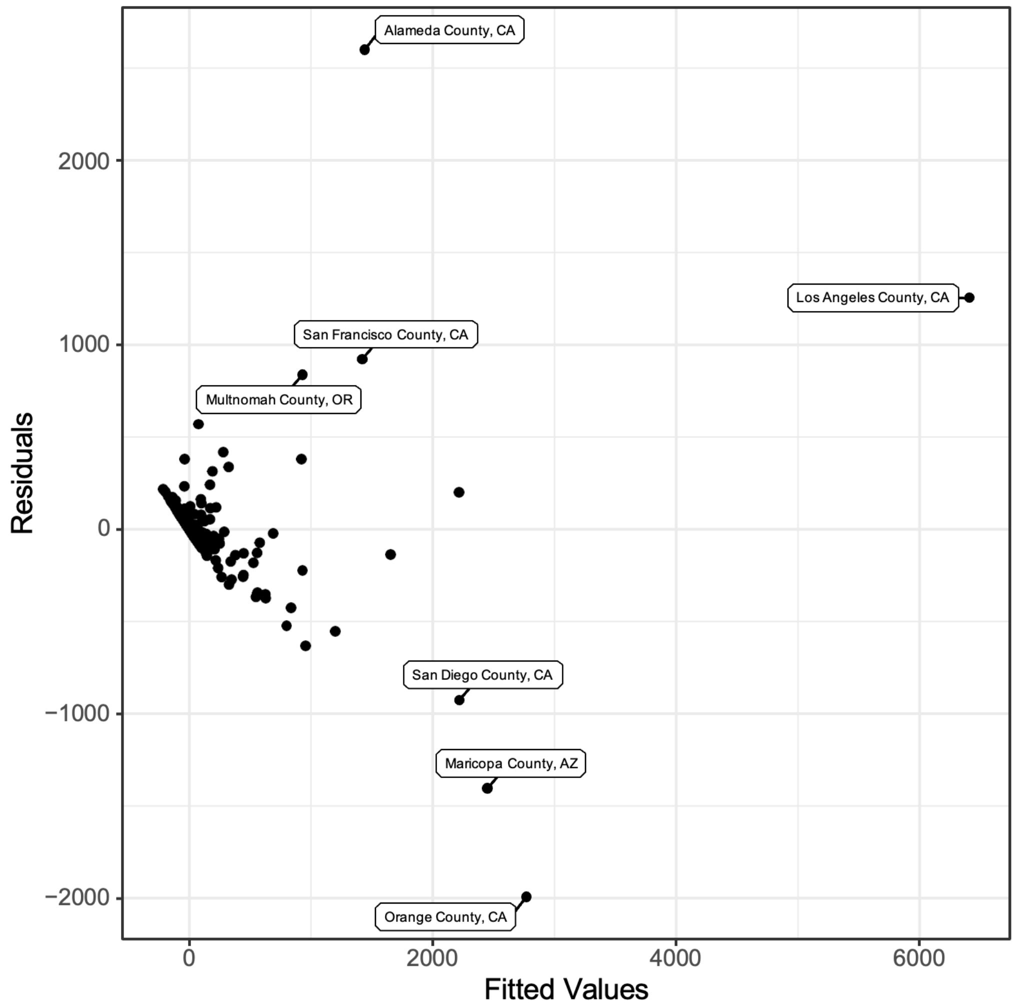
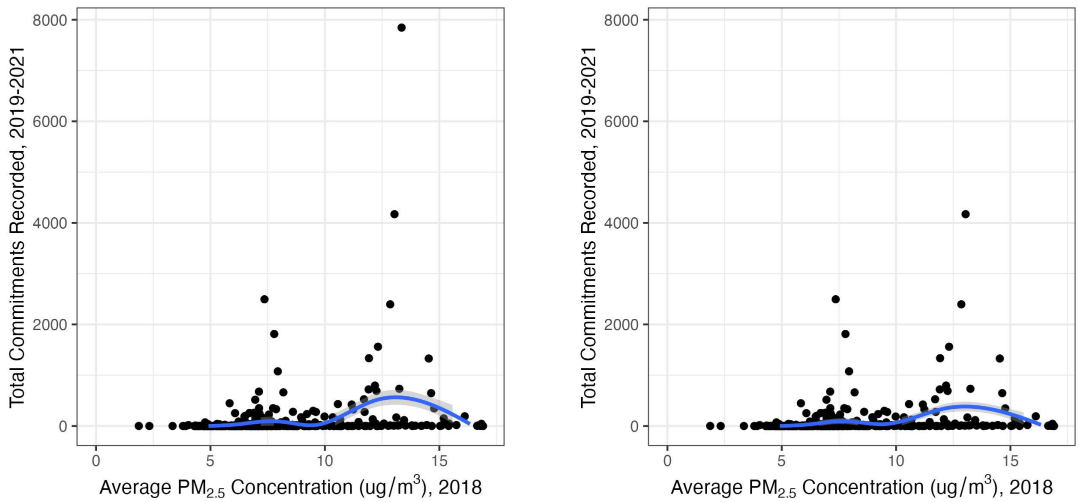


Figure E4: Investigating Functional Form



(a) Los Angeles County included in Sample

(b) Los Angeles County excluded from Sample