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The Public, Politics, and Pollution: Real-World Outcomes of Policy Responsiveness

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The Public, Politics, and Pollution: Real-World Outcomes of Policy Responsiveness

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To my wife, my brother, and my parents for their love and encouragement.

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The Public, Politics, and Pollution: Real-World Outcomes of Policy Responsiveness

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This dissertation advances a theory that brings real-world outcomes into our current understanding of the public opinion–policy responsiveness dynamic in both democratic and nondemocratic settings. The analysis examines a vital public good—air pollution remediation in American and Chinese localities—and estimates a dynamic model of relationships among three key variables: public opinion, policy, and air pollution outcomes. It focuses on both public opinion and air pollution outcomes as dependent variables. In both the United States and China, I find that local public opinion's impact on local air pollution is substantively meaningful, which suggests the additional policy effort prompted by public opinion is sufficient to yield tangible real-world outcomes in both cases. I also find that US public opinion reacts to changes in both policy and local pollution, and Chinese public opinion reacts to local pollution while ignoring available information about policy. I argue throughout the dissertation that the public informs its opinions with whatever credible information is readily at hand. In Chapter 4, I argue that China's public ignores the information available through official channels because the public correctly judges it to be objectively unreliable. I theorize that citizens can accurately assess information trustworthiness in issue domains that are visible in daily life; in such domains, citizens can evaluate a body of information's overall reliability based on how well it accords with their direct observations of the world around them.

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Chapter 1

Introduction

Policy responsiveness is an important concept in political science. Understanding the major factors that drive the actions of those in power is fundamental to the study of politics, and democratic political theory is based on the principle that the actions of government should reflect popular opinion. Practically speaking, however, policy responsiveness only matters to the extent it yields meaningful real-world outcomes.

Despite their obvious importance, little is known about the real-world outcomes of responsive policy. This may seem surprising given that both the opinion–policy and policy–outcomes relationships have been studied so extensively. However, neither relationship by itself indicates how much of the policy effort spurred by public opinion translates into tangible outcomes. This is true of the opinion–policy relationship because outcomes cannot be reliably inferred from policy itself. Policies' outcomes are inherently unpredictable to some degree—policy interacts with real-world conditions in complex ways that cannot be perfectly predicted. Indeed, policy outcomes vary dramatically; while many policies broadly achieve their goals, it is also common for policies to fall short or even be counterproductive (see, for example, McDermott et al. 2019; Ranson et al. 2015). This innate unpredictability is compounded by measurement limitations. The responsiveness scholarship's policy measures are based on formal aspects of policymaking like legislation and budgets. Such measures do not necessarily reflect the degree to which officially enacted policies are actually implemented. Policies can be formally enacted without being meaningfully carried out, and implementation efforts can vary dramatically without changes in formal policy (Gulzar and Pasquale 2017).

Policy responsiveness' real-world outcomes also cannot be inferred from the policy–

outcomes relationship. Policy changes can be prompted by both public opinion and objective problem severity, which is an outcome of policy (Bromley-Trujillo and Poe 2018; Bromley-Trujillo, Holman, and Sandoval 2019; Mullin 2008). One therefore cannot reasonably assume that the policies examined by the policy evaluation literature are caused by—or are even consistent with—public opinion. In short, the responsiveness scholarship establishes that some policy is prompted by public opinion, and the evaluation scholarship shows that some policy is effective. But this literature does not establish how much of the policy prompted by public opinion is effective.

The overarching goal of this dissertation is to bring policy's real-world outcomes into our current understanding of the public opinion–policy responsiveness dynamic. To this end, I develop and test a model that brings public opinion, policy, and outcomes into a single dynamic system. Incorporating policy outcomes—which are real-world conditions—advances our understanding of dynamic responsiveness in two important ways. One is that it allows for estimation of responsiveness' outcomes. Determining the degree to which responsiveness actually matters is itself important. It also opens the door for future scholarship to advance our understanding of this responsiveness further (e.g., identifying key factors that facilitate and impede meaningful responsiveness, and making comparisons across political systems). The second is that it makes it possible to differentiate between the effects of policy itself and policy's outcomes on public opinion. This has broad implications for understanding what information the public uses to develop its opinions as well as how the interplay between what the public wants and what it gets plays out over time.

1.1 Public Opinion and Information

The public must have coherent opinions for policy to be responsive. Even the most altruistic, earnestly responsive officials cannot respond to opinions that are logically paradoxical, hopelessly unstable, or simply nonexistent. Government officials also have less incentive to be responsive to citizens who have too little information to hold them

accountable for their actions.

If responsiveness is to be substantively meaningful, the public must form its opinions with information that has some basis in reality. It is of course possible for citizens to form opinions with information that is grossly inaccurate, or perhaps even without any information at all. And government officials could conceivably respond to such opinions. But such opinions are inherently arbitrary. By their nature, opinions that are untethered from reality cannot reliably guide policy towards desirable real-world outcomes.

The public obtains information from both media and direct observations in daily life. While large bodies of scholarship have established that citizens use information from both sources to form opinions, the relative importance of these two sources is unclear. Studies that examine media and responsiveness imply that the media is the only source that really matters. They find that policy responsiveness decreases or disappears entirely in the absence of media reporting, which implies the public lacks other viable information sources in the cases they look at (Barabas and Jerit 2009; Hiaeshutter-Rice, Soroka, and Wlezien 2019; Neuner, Soroka, and Wlezien 2019; Snyder and Strömberg 2010; Williams and Schoonvelde 2018).

Yet scholars have also found that responsiveness is fairly common in other settings in which citizens cannot obtain reliable information through the media—which strongly suggests the public does not always depend exclusively on the media for information. Street-level bureaucrats and local officials in the United States (US) and Brazil, for example—who typically receive little public scrutiny—are often sensitive to popular opinion and demands (Berkman and Plutzer 2005; Janvry, Finan, and Sadoulet 2010; Mladenka 1981; Percival, Johnson, and Neiman 2009). Policy responsiveness is even somewhat commonplace in authoritarian political systems where governmental secrecy, pervasive censorship, and murky lines of accountability obfuscate citizens' view of authorities' policy efforts (Chen, Pan, and Xu 2016; Gandhi and Przeworski 2006; Malesky and Schuler 2010; Miller 2015).

Why does the media appear to be the public's only viable information source in

some cases but not others? The logic underlying this study is that the public forms its opinions with whatever seemingly reliable information is accessible. When robust media reporting provides easy access to information about policy, it makes sense for the public use that information. When policy's outcomes are apparent in daily life, it makes sense for citizens to use that information as well. The public may use information from one source, both sources, or neither source, depending on the information's availability and credibility.

A key implication of this logic is the following two-fold arguement I make throughout this dissertation. It applies to policy domains with outcomes that are discernible to citizens in their daily lives. First, policy responsiveness in these domains can be ongoing and substantively meaningful to the general public even when citizens lack reliable policy information from the media. Second, this responsiveness is possible because citizens can use direct observations of real-world conditions to form coherent opinions about whether the government should do more (or less) to address an issue.[1]

1.2 Dynamic Responsiveness

Existing scholarship models dynamic responsiveness as a system with two parts: public opinion and policy. In this system, changes in public opinion lead to changes in policy, which lead to further changes in public opinion in an ongoing process. The public's preference for further increases (decreases) goes down when the government does more (less) about an issue (Jennings 2009; Pacheco 2013b; Soroka and Wlezien 2005; Soroka and Wlezien 2010; Wlezien 1995; Wlezien and Soroka 2012)—assuming the public's preferred level of policy remains constant.

The public's preferred level of policy does not remain constant, of course. It evolves over time. This fact is widely recognized and is explicitly acknowledged in some of the

[1]Citizens may also use these direct observations to evaluate the performance of governing officials and hold them accountable through whatever mechanisms are available to them (e.g., elections and collective action).

literature on dynamic responsiveness. These shifts, however, are not accounted for in the empirical models of the dynamic. Explicitly modeling real-world conditions as part of the dynamic helps to address this problem, for they are a major factor that shapes preferred policy levels. Generally speaking, worsening conditions increase the public's preferred policy level while improving conditions have the opposite effect.

Including real-world conditions along with policy as an explanatory variable (EV) for public opinion has important practical implications for statistical models. Policy and real-world conditions are closely associated—policy change shifts conditions (sometimes in unintended ways), and shifts in conditions can prompt policy change. When policy works as intended, policy and conditions move together and push public opinion in the same direction. Increased policy causes the public's preference for further increases to go down, and the improved conditions created by the increased policy decrease the public's preferred level of policy. In this scenario, adding conditions as an EV's makes little difference in explaining public opinions variation. When policy does not work as intended—perhaps because it was counterproductive or failed to overcome external factors—policy and conditions move in opposite directions and push public opinion in opposing directions. In this scenario, policy increases as conditions worsen. The policy increase would cause the public's preference for further increases would go down, ceteris paribus, but the worsening conditions increase the public's preferred level of policy. In cases like this, including conditions would dramatically improve model performance both in terms of explaining public opinion's variation and accurately estimating the EV's.

1.3 Empirics

1.3.1 Issue Domain

The analysis in the following chapters focuses on air pollution remediation. This issue area is particularly well suited for the purposes of this study. Policy outcomes in this domain are pollution levels, which can be objectively measured at a very high spatial and temporal resolution. Air pollution is directly observable by citizens in daily life. This

makes the issue well suited for accessing both the real-world outcomes of policy and the impact of those outcomes an public opinion.

The findings in this domain may generalize to other issues that involve public goods and highly visible outcomes, which can be investigated by future research. Such domains may include other aspects of local environmental quality (e.g., drinking water safety) and local infrastructure (road and transportation quality).

1.3.2 Statistical Analysis

The statistical analysis centers on estimating the relationships between public opinion, policy effort, and outcomes. The basic framework for the statistical models is a system of three equations in which each of these variables is a function of the other two. The dependent variables of greatest interest are air pollution outcomes and public opinion. After accounting for non-policy factors (e.g., economic output and emissions from outside sources), year-on-year changes in local air pollution reflect the real-world outcome of policy efforts in a given locality. And after accounting for policy efforts prompted by air pollution severity itself, one can estimate the real-world impact of the policy efforts driven by public opinion.

1.3.3 Cases

Chapters 2 and 3 examine localities in the United States (US) and China respectively. Both countries provide difficult test cases for the hypotheses that follow from the model I develop. This is especially true of China, which ranks among the most authoritarian countries in the world—it lacks any meaningful electoral mechanisms and frequently punishes citizens who undertake other forms of political participation. Even in the US—which is a liberal society with competitive elections—there are substantial institutional impediments to responsiveness at the local level. Local-level political authority in the US is spread across a dizzying assortment of governing bodies with overlapping jurisdictions, many of which are gerrymandered. This makes it more difficult for citizens to assigning

responsibility to government officials and hold them accountable difficult.

Both cases have information environments that limit citizens' access to reliable policy information. The US is characterized by a scarcity of information about local matters—the long term decline of local media coverage in the US is widely recognized. China is characterized by abundant—but unreliable—information about local matters. Chinese local governments have large propaganda apparatuses that disseminate information about the activities of local officials and the effectiveness of their policies. This information is objectively unreliable (see Chapter 4).

This contrast in the two countries' information environments is useful for examining whether the public simply forms its opinions with whatever information is readily available, or whether the public also evaluates the reliability of the available information. In China, I find that public opinion reacts to local air pollution, but not the policy information disseminated by the government. In the US, on the other hand, I find that the public used all of the major sources of information available. I argue in Chapter 4 that these results are evidence that citizens can correctly assess information reliability when policy outcomes are visible in daily life. As discussed in that chapter, this may be possible because citizens can validate information reliability based on how well the information conforms with their direct observations.

1.3.4 Time Scales of Responsiveness

Policy responsiveness can occur on any time scale, so it is worth explaining why the analysis in this dissertation focuses on year-on-year changes and single year lags. Time scales shorter than a year are off the table for any model with air pollution as a dependent variable. Air pollution is sensitive to seasonal effects that are best dealt with by annualizing the daily measures.[2] The length of the currently available time series imposes limits on analyzing responsiveness on longer time scales. The time series extends from 2010 through 2018 for the United States and 2011 through 2015 for China.

[2]Public opinion reacts to air pollution changes on time scales much shorter than a year.

Nevertheless, it is important to bear in mind that the turnaround time of responsive policy in the context of this analysis—i.e., the average time between a public opinion changing and the resulting policy change yielding real-world outcomes—is more than a single year.

The immediate practical implication of the one year lags used in this study is that public opinion's impact on outcomes (via responsive policy) will be smaller and harder to detect than it likely is on larger time scales. This biases the results *against* substantively meaningful responsiveness.

While type 1 error is not a concern, the timescale(s) on which responsiveness plays out remains an interesting matter worth exploring. As I touch on in Chapters 2 and 3, the effect sizes and the types of governmental actions that appear to be responding to public opinion imply a minimum turnaround time of around two or three years. Of course, many actions governments take to mitigate air pollution, like investments in public transportation, take much longer to yield results. The timescales of responsiveness should be more thoroughly explored by future studies with longer time series.

1.4 Findings and Implications

The findings indicate substantively meaningful responsiveness in both countries. A one standard deviation shift in local public opinion is sufficient to yield local air pollution changes that are large enough to be perceptible in daily life within two to three years. Over the longer term, effects of this magnitude can profoundly effect public health.

As independent media has declined in the face of economic pressures and rising authoritarianism around the world, there is a pervasive sense of pessimism regarding the future of responsive government. After all, scholarship has established that decreased reporting by independent media reduces citizens' policy knowledge, reduces the responsiveness of government officials and the electoral competition they face, and increases corruption (Fraile and Iyengar 2014; Gao, Lee, and Murphy 2020; Hiaeshutter-Rice, Soroka, and Wlezien 2019; Rubado and Jennings 2019; Snyder and Strömberg 2010; Williams and

Schoonvelde 2018).

Against this bleak backdrop, the study presented here is cause for modest (and qualified) optimism. It finds that without policy information from robust media reporting, citizens can still form coherent opinions, which is a necessary (though not sufficient) condition for responsiveness. The results also show substantively meaningful responsiveness continues to exist across hundreds of US localities—despite decades of media atrophy—and in China, one of the most authoritarian countries in the world. The overall consistency of the results in two such dissimilar countries—with different political systems, levels of development, and pollution magnitudes—suggests that these findings are highly generalizable across locations and over time.

This is not to say that media reporting is inconsequential for responsiveness. Far from it. I argue that the visibility of policy outcomes in daily life is what allows the public to form opinions with minimal policy information from media reporting. While many issues have easily discernible outcomes (e.g., local air and water quality, road maintenance, and school performance), many others do not (e.g., financial regulation and foreign policy). Furthermore, the information citizens can infer from outcomes alone tends to have far less context and detail than reporting by teams of professional journalists. Thus, responsiveness is likely to be stronger in the presence of more robust media coverage even in issue domains with highly visible outcomes.

Chapter 2

The United States

Policy responsiveness is a dynamic process when the public has easy access to relevant information—public opinion both reacts to policy and affects policy (Bonafont and Palau 2011; Jacoby and Schneider 2001; Jennings 2009; Jones, Larsen-Price, and Wilkerson 2009; Schneider, Jacoby, and Lewis 2011; Soroka and Wlezien 2010; Wlezien 1995; Wlezien and Soroka 2012). The extent to which responsiveness exists when the public lacks policy information is poorly understood. A large body of literature implies that citizens need policy information to form opinions and hold government officials accountable. Indeed, studies have shown that responsiveness diminishes when such information is restricted (see, for example, Gao, Lee, and Murphy 2020; Lax and Phillips 2012; Pacheco 2013b; Rubado and Jennings 2019; Snyder and Strömberg 2010).

Yet scholars have also found policy to be at least ostensibly responsive in many cases in which only minimal policy information is available to citizens. Street-level bureaucrats and local officials in the United States (US) and Brazil, for example—who typically receive little public scrutiny—are often sensitive to popular opinion and demands (Berkman and Plutzer 2005; Janvry, Finan, and Sadoulet 2010; Mladenka 1981; Percival, Johnson, and Neiman 2009). Policy responsiveness is even somewhat commonplace in authoritarian political systems where governmental secrecy, pervasive censorship, and murky lines of accountability obfuscate citizens' view of authorities' policy efforts (Chen, Pan, and Xu 2016; Gandhi and Przeworski 2006; Malesky and Schuler 2010; Miller 2015).

How can policy responsiveness be so common when citizens lack policy information? One possibility is that citizens do not always need information about policy itself to form coherent opinions and hold authorities accountable. A second possibility is that

the responsiveness scholars have found in low-information settings is statistically but not substantively significant. If citizens lack sufficient information to form opinions and hold officials accountable, responsiveness will tend to be superficial or narrowly targeted at small, hyper-informed constituencies. Extant scholarship does not discount this scenario; most of the responsiveness scholars have found in low-information settings involves the provision of private goods to individuals and small groups with political leverage (see, for example, Chen, Pan, and Xu 2016; Jones et al. 1977; Zuckerman and West 1985), and the real-world impacts of responsive policy on the general public have not been established in the literature.

To address this matter, I propose a dynamic model of responsiveness that extends to circumstances in which citizens have only very limited information about policy itself. A novel feature of this model is that it brings together public opinion, policy, and policy's real-world outcomes into a single dynamic system. Both the opinion–policy and policy–outcomes relationships have been well studied, but neither relationship by itself indicates how much of the policy effort spurred by public opinion translates into tangible outcomes. This is true of the policy–outcomes relationship because policy changes are prompted by both public opinion and objective problem severity, which is an outcome of policy (Bromley-Trujillo and Poe 2018; Bromley-Trujillo, Holman, and Sandoval 2019; Mullin 2008). This is also the case for the opinion–policy relationship because some policies are better implemented and more effective than others (Gulzar and Pasquale 2017; McDermott et al. 2019; Ranson et al. 2015). Thus, the literature shows that public opinion drives some policy, and that some policy is effective, but it does not establish how much effective policy is prompted by public opinion.

The argument I make with this model is two-fold and applies to policy domains with outcomes that are discernible to citizens in their daily lives. First, policy responsiveness in these domains can be ongoing and substantively meaningful to the general public even when citizens lack information about policy itself. Second, this responsiveness is possible when policy information is inaccessible because citizens can use direct observa-

tions of outcomes to form coherent opinions about whether the government should do more (or less) to address an issue.[1]

To test this model, I look at an important public good with outcomes that are both objectively measurable and visible to citizens in everyday life: air pollution. Air pollution is an ideal issue domain for assessing the impact of policy responsiveness on the public as a whole and not just influential constituencies. Because air pollution is fluid, policy can strongly influence its overall level in a locality (Ranson et al. 2015), but can do little to target it at specific constituencies.[2]

My empirical strategy centers on estimating the relationships between public opinion, policy effort, and air pollution outcomes in 319 localities in the US from 2010–2018. These are all the localities for which data are available. Estimating the relationships between public opinion, policy, and outcomes is done using both standard ordinary least squares (OLS) regressions and structural equation models (SEM's), which can account for the error correlation and biased estimates that may result from feedback dynamics. To measure air pollution outcomes, I use satellite-derived concentrations of two ubiquitous pollutants: nitrogen dioxide (NO_2, which is a key component of smog) and fine particulate matter ($PM_{2.5}$). The policy measurement is the number of disciplinary actions for Clean Air Act (CAA) violations that take place in a state or locality each year. Public opinion is measured with the Google Trends internet search index, which reflects issue salience by indicating the annual proportion of air pollution-related searches in each state and locality. While relatively new to the social sciences, scholarship has established that search indexes like Google's are valid measures of issue salience (see Mellon 2013; Oehl, Schaffer, and Bernauer 2017; Reilly, Richey, and Taylor 2012; Swearingen and Ripberger 2014); it also has vastly higher spatial and temporal resolution than is possible with surveys.

[1] Citizens may also use these direct observations to evaluate the performance of governing officials and hold them accountable through whatever mechanisms are available to them (e.g., elections and collective action).

[2] Governing authorities are not entirely powerless to shield favored constituencies from pollution exposure within a locality, but within-locality air pollution variation demonstrates serious practical limitations on their ability to do so (see Pinault et al. 2016).

The dependent variables of greatest interest are air pollution outcomes and public opinion. After accounting for non-policy factors (e.g., economic output and emissions from outside sources), year-on-year changes in local air pollution reflect the real-world outcome of policy efforts in a given locality. And after accounting for policy efforts prompted by air pollution severity itself, one can estimate the real-world impact of the policy efforts driven by public opinion. I find that policy is sufficiently responsive to local public opinion to meaningfully affect the public's welfare—a one standard deviation shift in public opinion affects air pollution enough to be perceptible to citizens and affect public health within two to three years.

This responsiveness to local public opinion raises the question of how citizens obtain enough information about local matters to form coherent opinions and hold officials accountable.[3] For national and statewide matters, media reporting provides an obvious source of policy information for the public, and there is ample evidence that it is the dominant mechanism through which the public gets information about policy itself (Barabas and Jerit 2009; Hiaeshutter-Rice, Soroka, and Wlezien 2019; Neuner, Soroka, and Wlezien 2019; Williams and Schoonvelde 2018).

Media reporting is a far less viable mechanism for informing citizens about local affairs. The decline of traditional media at the local level in the US (and elsewhere) in recent decades is widely recognized, and new forms of media have not replaced it as a source for local policy-related information (Hindman 2011). Much of the local media coverage that still exists is heavily biased towards covering national-level issues (Kaplan,

[3]Forming coherent opinions about whether the government should do more (or less) about an issue is nearly impossible without any information related to existing policy efforts (Hiaeshutter-Rice, Soroka, and Wlezien 2019; Williams and Schoonvelde 2018). The public may still form opinions without relevant information, of course, but such opinions are inherently arbitrary. By their nature, arbitrary opinions cannot reliably guide even the most earnestly responsive government officials toward achieving desirable real-world outcomes.

Government officials also face fewer incentives to be responsive to public opinion in the absence of feedback. Citizens have various tools they can use to hold officials accountable, like voting and collective action—but citizens can only use these tools effectively if they are at least vaguely aware of government officials' activities. Thus, without the public having some form of policy-relevant information, responsiveness tends to be weak and yield ineffective policy efforts.

Goldstein, and Hale 2005). The consequences of weak local media have also been well documented in the form of increased waste and corruption by local governments after the closure of local newspapers (Gao, Lee, and Murphy 2020).

To address the question of where the public obtains the information necessary for responsiveness, I estimate the effects of air pollution and policy on local public opinion. After controlling for outcomes, public opinion's sensitivity to objectively measured policy indicates the extent to which the public uses information about policy itself to form its opinions. And after controlling for policy, public opinion's sensitivity to outcomes indicates the extent to which the public bases its opinions on information about policy's outcomes.[4]

I find that public opinion reacts to local air pollution as well as statewide policy efforts. The public's sensitivity to statewide policy suggests that citizens inform their opinions with information about policy itself (likely obtained through the media). The public's sensitivity to local air pollution outcomes suggests that citizens also use outcomes they can directly observe in daily life to inform their opinions—and that they can use direct observations to form opinions even when they lack information about policy itself, which is often inaccessible at the local level due to weak media reporting in most localities. More broadly, these results imply that the public informs its opinions with whatever relevant information is easily accessible. When policy outcomes are visible in daily life, citizens use their direct observations of those outcomes to inform their opinions. When professional media reporting provides information about policy itself, citizens use that information too.

2.1 Outcomes of Responsive Policy

While the size of responsiveness' real-world outcomes is most in doubt for settings with minimal policy information, little is known about them in *any* information environ-

[4]It is necessary to look at policy and outcomes' effects together because they are closely associated; policy affects outcomes and air pollution severity prompts some policy.

ment. Even when information is easily accessible, extending the logic of the responsiveness literature to include outcomes leads to ambiguous expectations about their magnitude. On the one hand, responsiveness to the public's priorities appears to decrease as one moves farther into the policy process (Bonafont and Palau 2011; Jones, Larsen-Price, and Wilkerson 2009), which implies that responsiveness is quite small—even negligible—at the implementation and outcome stages. On the other hand, spending levels respond to changes in public preferences across policy domains (Jennings 2009; Pacheco 2013b; Soroka and Wlezien 2005; Soroka and Wlezien 2010; Wlezien 1995; Wlezien and Soroka 2012). Given that spending levels affect the enforcement actions by government agencies (Wood and Waterman 1993), this implies outcomes are responsive to some degree. There is, however, little indication of the magnitude we should expect. While dramatic changes in spending levels like defense buildups and disaster responses almost certainly produce meaningful outcomes, such extreme spending changes are rare (Jones et al. 2009). The literature is unclear as to how responsive outcomes are likely to be to more routine policy adjustments driven by shifts in public sentiment.

2.2 Theoretical Model

I propose a dynamic model of responsiveness that incorporates real-world outcomes and extends to settings in which the public has only limited policy information. The model applies to domains with outcomes that are discernible to citizens in their day-to-day lives.

Regarding terminology, *public concern* refers to an issue's salience and the public's preference for the government to do more to address it. In many issue areas—particularly technical domains—public attention to the issue and the degree to which it prefers the government to do more about it go hand in hand (Oehl, Schaffer, and Bernauer 2017).[5] *Policy effort* refers to the aggregation of governmental activities related to an issue in

[5]This is, of course, not the case for highly divisive issues, which are salient and lack popular consensus as to what (if anything) the government should do to address them.

a given location. It is a broad conception of policy and is discussed further in the next section.

I make a two-fold argument with this model. One, policy responsiveness can be substantively significant for the general public's welfare even when citizens have little information about policy itself. Two, this responsiveness is possible because citizens can form grounded opinions and evaluate the performance of government officials based on the policy outcomes that are discernible in daily life. The first part of this argument can be expressed as two hypotheses:

1. Increased (decreased) public concern with an issue increases (decreases) the government's overall level of policy effort addressing it.

2. The additional policy effort prompted by public concern meaningfully mitigates problem severity (i.e., affects outcomes) in that issue domain.

Hypothesis 1 expresses the consensus of the policy responsiveness scholarship for important issue domains (Berkman and Plutzer 2005; Bonafont and Palau 2011; Janvry, Finan, and Sadoulet 2010; Jacoby and Schneider 2001; Jennings 2009; Jones, Larsen-Price, and Wilkerson 2009; Lax and Phillips 2012; Mladenka 1981; Pacheco 2013b; Percival, Johnson, and Neiman 2009; Schneider, Jacoby, and Lewis 2011; Soroka and Wlezien 2010; Wlezien 1995; Wlezien and Soroka 2012). Hypothesis 2 addresses the substantive outcomes of the responsive policy, which remain poorly understood in the literature. Policy often achieves its intended outcomes (Ranson et al. 2015). Some policy efforts, however, are prompted by experts' assessment of problem severity itself as opposed to public opinion (Mullin 2008), and policy's effectiveness can vary wildly (Gulzar and Pasquale 2017; McDermott et al. 2019). One therefore cannot infer from extant scholarship the extent to which the policy efforts prompted by public concern meaningfully affect outcomes.

My argument's second aspect is that citizens form their opinions with relevant information that is readily available. To be more specific:

3. Policy has a robust effect on public concern when citizens have easy access to information about policy itself.

4. Policy outcomes that are discernible in daily life have a robust effect on public concern even when citizens lack information about policy itself.

Hypothesis 3 is unambiguously supported by the literature (Barabas and Jerit 2009; Jerit, Barabas, and Bolsen 2006; Williams and Schoonvelde 2018). This scholarship establishes that media reporting is the dominant mechanism for informing the public about policy (Eveland 2002; Hiaeshutter-Rice, Soroka, and Wlezien 2019), and is discussed further in the Mechanisms section.

For Hypothesis 4, the scholarly evidence is less clear-cut than it is for hypotheses 1 and 3. It is well known that outcomes affect public opinion, but Hypothesis 4 posits that this effect is *robust*. While some studies have found a strong effect (Janvry, Finan, and Sadoulet 2010; Egan and Mullin 2012; Kim et al. 2020; Stokes 2016), others have found it to be quite weak (Ansolabehere, Meredith, and Snowberg 2014; Bergquist and Warshaw 2019; Borick and Rabe 2010)—sometimes to the point of being entirely drowned out by the effect of policy itself (Soroka and Wlezien 2010, 107–124). The reason for these divergent findings has not been well explored in the literature. But when taken together, these studies imply that citizens react strongly to outcomes that are discernible in daily life and weakly (or not at all) to those that are not. Studies that aggregate outcomes over large geographic areas (such as nations or American states) find weak or insignificant effects. Studies that measure outcomes at the local level, where they are most proximate to citizens' daily lives, tend to find much stronger effects.

As noted above, the model's underlying logic is that the public forms preferences for more (or less) policy in an issue area with whatever relevant information is readily at hand. When information about policy itself is readily available (due to robust media reporting, for example), citizens use that information to develop their opinions. When

citizens directly observe policy's real-world outcomes in their daily lives, they use that information as well.

Figure 3.1 provides an overview of the theoretical model for four different information environments. In the upper two subfigures (*a* and *b*), citizens can directly observe outcomes in their day-to-day lives. Outcomes are not directly observable in the lower two subfigures (*c* and *d*). In the left-hand subfigures (*a* and *c*), the public has access to information about policy itself through the media. Citizens lack policy information in the right-hand subfigures (*b* and *d*). Figure 3.1 reflects that citizens make use of the information they have at hand; the information the public does not react to (represented by relationships with dashed lines) is information it lacks easy access to. The figure also conveys that substantive responsiveness is possible so long as citizens have information that—directly or indirectly—reflects governmental policy efforts. Substantive responsiveness (relationships *i* and *ii*) is robust in subfigures *a*, *b*, and *c*. Meaningful responsiveness only becomes impossible when citizens lack information about policy itself *and* cannot infer governmental efforts (and performance) through direct observations in daily life (subfigure *d*).[6]

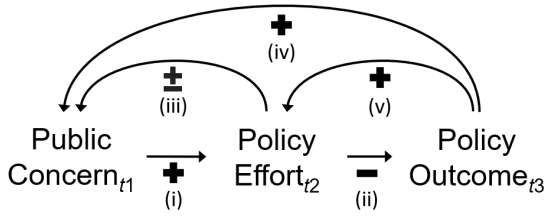
Note that relationship *iii*'s plus-minus (±) sign indicating that the sign of the relationship is ambiguous. A negative sign means that when the public sees the government doing more (less) about an issue, the public's preference for further increases (decreases) goes down. A positive sign means that the public seeing the government doing more about an issue *strengthens* the public's desire for further policy efforts. In real-world settings, this sign tends to be negative (Jennings 2009; Wlezien and Soroka 2012), but this is by no means always the case (see Pacheco 2013a). My theory is agnostic as to the sign of relationship *iii*.

Note also the signs of the relationships involving policy outcomes (relationships

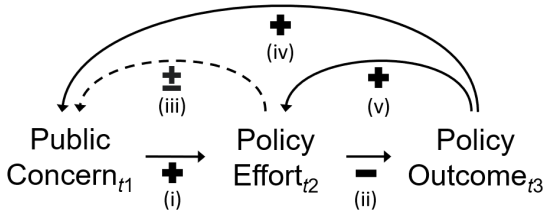
[6]There are no hypotheses associated with Subfigure *d*, for none of its relationships are empirically tested in this study. Nevertheless, it follows the logic of my theory and can be empirically tested in future research.

Figure 2.1: Theoretical Model Overview

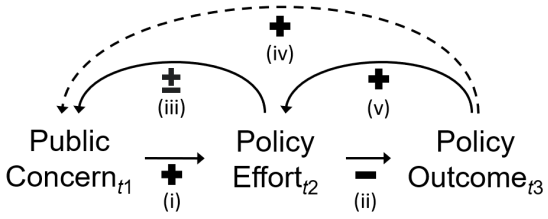
(a) Policy Info. & Visible Outcomes



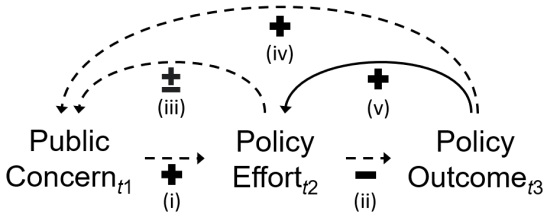
(b) No Policy Info. & Visible Outcomes



(c) Policy Info. & No Visible Outcomes



(d) No Policy Info. & No Visible Outcomes



Note: The arrows with plus (+) and minus (−) signs represent theorized positive and negative causal relationships respectively. Plus-minus (±) indicates that the relationship's sign is ambiguous. The dashed arrows signify what are expected to be the weaker of the two effects on public concern. $t1$, $t2$, and $t3$ represent periods in time. The arrows pointing from right to left (*iii*, *iv*, and *v*) represent a variable's effect on another in the following time period.

ii, *iv*, and *v*). *Policy outcome* is synonymous with problem severity in this figure—that is, higher levels of the outcome are contrary to the public's perceived interests. Policy outcomes can just as easily be defined as the opposite of problem severity, where higher levels are what the public wants. In that case, the signs of relationships *ii*, *iv*, and *v* would be flipped.

2.3 Conceptualizing Policy Effort

Policy effort refers to the aggregation of governmental activities related to an issue in a given location. Particularly in decentralized federal systems, the actions that constitute policy effort can be undertaken by multiple governing entities. These actions

are often intertwined to the point that they cannot be meaningfully disentangled. National regulations may be determined by the interplay between national-level authorities and the subnational authorities tasked with implementing them (Huang, Santibanez-Gonzalez, and Song 2018). State and local governments also lobby national authorities to take various action within and around their jurisdictions (Goldstein and You 2017).

Policy effort consists of both the formation of policy and its implementation (see Kingdon 1995). The former include political leaders' search for solutions, deliberation, and the formation of official policies, goals, and priorities. The latter include formal policy actions that explicitly affect implementation (e.g., allocating resources for monitoring compliance) and the actions of the political leadership's subordinates—particularly street-level bureaucrats and other low-level officials. Recognizing these two aspects of policy is important because they often do not closely correspond. Even at the budgeting stage of the policy process, there are often large discrepancies between the resources allocated to addressing issues and the amount actually spent (Wlezien and Soroka 2003). Local officials' implementation efforts of national policies can also vary dramatically by jurisdiction (Gulzar and Pasquale 2017).

Policy implementation itself takes both explicit and inexplicit forms. While this distinction is relevant in many policy domains, my discussion here centers on air pollution because it is relevant for the empirical analysis. *Explicit* implementation efforts are those that advance a clearly stated policy goal. Formal enforcement actions are common examples (e.g., regulators monitoring and fining violators of pollution emissions standards). *Inexplicit* efforts advance a goal that is not clearly stated. Inexplicit actions are inherently difficult to observe and directly measure. Even so, scholars have shown that the locations of pollution-intensive activities at the state and local levels concentrate pollution in areas with the least political leverage (Huang, Santibanez-Gonzalez, and Song 2018; Monogan, Konisky, and Woods 2016; Pargal et al. 1997; Pinault et al. 2016)—despite no apparent geographic bias in formal regulatory enforcement (Atlas 2001; Gray and Shadbegian 2004; Konisky and Woods 2010, 2012). As these scholars argue, this pattern strongly implies

that state and local authorities regularly use zoning rules, building permits, and other regulations and incentives to influence the behavior of polluters.

2.4 Mechanisms

This section discusses the causal mechanisms between the three variables of interest. It pays special attention to those that pertain to the empirical analysis: air pollution in the US.

2.4.1 Air Pollution Outcomes

Air pollution refers to the average concentration of air pollutants at ground-level within a state or locality. It is a function of policy effort. When governments do more to mitigate air pollution, pollution levels will be lower than they would otherwise be. The opposite is also true. It is important to note that while air pollution is a function of policy, policy is *not* the primary driver of a state or locality's pollution level—at least not in the short to medium term. The main determinants of an area's air pollution is its economic activity and geography (Chan and Yao 2008; Jiang, Lin, and Lin 2014; Jeong et al. 2017). Conceptually, one can think of policy as a force that pushes air pollution levels above or below a "natural" level that is determined by an area's economy and geography.

2.4.2 Public Concern

Media reporting is the dominant mechanism for informing the public about policy (Eveland 2002; Hiaeshutter-Rice, Soroka, and Wlezien 2019). While the quality of media sources varies (Druckman 2005; Fraile and Iyengar 2014), many national-level outlets accurately report the direction and magnitude of policy change (Soroka and Wlezien 2019), and citizens can identify and decode policy-related information in media coverage (Eveland 2002; Neuner, Soroka, and Wlezien 2019). The effects scholars have found of state-level policy change and performance on public opinion also strongly suggests that this relationship is not unique to national-level politics (Lyons, Jaeger, and Wolak 2013;

Pacheco 2013b). While there is far less media reporting at the local level overall, citizens likely use whatever is available there too.[7]

Information about policy outcomes can be obtained through the media as well. In the case of air pollution, however, the public can also directly observe the outcomes. Even short-term exposure to pollutants like NO_2 and $PM_{2.5}$ causes physical discomfort (Amundsen, Klæboe, and Fyhri 2008; Rotko et al. 2002). This physical discomfort may also prompt citizens to seek out more precise indicators of local air pollution. Even motivated amateurs can measure a number of common air pollutants and many localities in the US have air quality monitoring stations that provide freely available data in real time. Citizens may look up this information themselves or learn about it through word of mouth and online social platforms.

2.4.3 Policy Effort

Policy effort is a function of public concern and real-world outcomes (i.e., problem severity). Public concern's effect on policy is well established in many issue domains, including the environment (Basu and Devaraj 2014; Lubell et al. 2006; McCreery 2010; Wlezien 1995). The most obvious avenue through which public concern affects policy is the electoral system. Government officials tend to respond to changes in public opinion to win elections, and even when they lose, electoral turnover leads to the selection of political leaders whose preferences better reflect those of the public (Hakhverdian 2010). The actions of elected officials, such as setting budgets and making appointments, affect the implementation efforts of environmental regulators (Wood and Waterman 1993).

There are also subtler responsiveness mechanisms beyond the electoral system. Some elected officials genuinely want to represent the preferences of their constituents (Butler and Nickerson 2011). There is also evidence that bureaucrats tend to feel a sense of professional responsibility to respond to citizens preferences and demands. For example,

[7]Indeed, this is consistent with the media–public opinion relationship scholars have found in localities with significant media reporting (see, for example, Henry and Gordon 2001).

political appointees are often more responsive to public opinion than are directly elected officials (Berkman and Plutzer 2005), and local bureaucrats are frequently responsive to citizens' requests (Mladenka 1981).[8]

Policy effort is also prompted by problem severity itself. This is especially true of unelected technocratic bodies tasked with reacting to objective indicators of problem severity (Mullin 2008). This is also true—albeit it less consistently—of elected officials (Bromley-Trujillo, Holman, and Sandoval 2019), who may use objective indicators of problem severity to rationally anticipate changes in voters' preferences and priorities (Hakhverdian 2010).

Responsiveness can occur at any point in the political system and affect both explicit and inexplicit forms of policy. Elected officials and responsive bureaucrats vary their enforcement efforts and sometimes modify emissions standards at the national level (Auffhammer and Kellogg 2011; Ranson et al. 2015; Wood and Waterman 1993), and local public pressure and governing priorities affect how rigorously national standards are enforced subnationally (Basu and Devaraj 2014; Sjöberg 2016; Woods and Potoski 2010).

2.5 Measuring Variables of Interest

Most of the variables in this analysis are aggregated at both the state and local level.[9] Localities are defined as the metropolitan core-based statistical areas (CBSA's) set by the Office of Management and Budget (OMB) in 2015. Metropolitan CBSA's are urban areas in the US with over 50,000 people and the surrounding counties from which they draw commuters. They are socioeconomic entities, not political jurisdictions. They are appropriate units for this study because there is no unified political authority at

[8]This scholarship identifies a wide range of mechanisms by which government officials are made aware of public sentiment. These include election outcomes, public opinion polls, social interactions with local constituents, and members of the public confronting officials face to face. The relative importance of these mechanisms is unimportant for my model, which only requires that officials use some combination of them to form a general sense of public sentiment.

[9]See Appendix A.1 for summary statistics.

the local level, and the policy efforts that affect local air pollution can come from any combination of governing entities.

2.5.1 Public Concern

Public concern is measured with the Google Trends index of internet searches related to air pollution, which has higher nationwide spatial and temporal resolution than is possible with surveys. The index represents the annual number of air pollution-related searches relative to the total search volume in a geographic area.

For the primary models presented in this paper, the search index values are for the following combination of terms: *smog + no2 + air pollution + ozone + pm2.5 + AQI*. In Appendix A.2, I show results that drop the sixth search term—*AQI*—to demonstrate robustness. The SEM's use the latter combination of five search terms, as using all six created issues with maximum likelihood estimation converging.

Fundamentally, a search index reflects an issue's salience (Mellon 2013), which does not necessarily indicate the public's preferences for government action on a given issue. However, as pointed out above, salience does correspond to the public's preference for the government to do more in technical issue domains like air pollution. Google's search index has been found to be a reliable indicator of public preferences for government action on environmental issues cross-nationally (Oehl, Schaffer, and Bernauer 2017).

2.5.2 Policy Effort

Policy Effort is measured by aggregating all enforcement actions of the Clean Air Act (CAA) recorded by the Environmental Protection Agency (EPA) that take place in a state or locality each year. These enforcement actions consist of ongoing federally reportable violations (FRV's), ongoing high priority violations (HPV's), formal disciplinary actions (e.g., issuing fines), and informal disciplinary actions (e.g., issuing notices of non-compliance).[10]

[10] https://echo.epa.gov

These actions can be undertaken by authorities at any level of the political system. Most (over 70 percent) of these actions are executed by state-level authorities, and the remainder are by authorities at the national and local levels. The measure consists of all actions that take place within a state or locality, regardless of which levels of the political system executes them.

2.5.3 Air Pollution Outcomes

I measure ground level air pollution outcomes with two ubiquitous pollutants—NO_2 and $PM_{2.5}$—which are indicative of a locality's overall air pollution level. NO_2 and $PM_{2.5}$ typically have correlations of over 0.7 with other major air pollutants, including course particulate matter (PM_{10}), carbon monoxide (CO), and sulfur dioxide (SO_2) (Guo, Wang, and Zhang 2017). The correlation between NO_2 and $PM_{2.5}$ in my sample is 0.7.

Ground level NO_2 is better suited for the purposes of this study because it has greater spatial variation and is more sensitive to local events (Jeong et al. 2017). $PM_{2.5}$ is an unusually long-lived pollutant that is prone to traveling hundreds of kilometers before dropping out of the lower atmosphere. Nevertheless, $PM_{2.5}$ provides a useful robustness check for the sensitivity of outcomes to responsive policy because it is derived from different satellite instruments using different methods.

I calculate each locality's annual NO_2 and $PM_{2.5}$ concentrations with daily satellite overpass data. The NO_2 data are from the DOMINO (version 2) and TM4NO2A (version 2.3) datasets provided by the European Space Agency. The $PM_{2.5}$ data are from the Global Annual $PM_{2.5}$ Grids provided by NASA's Socioeconomic Data and Applications Center.[11]

These satellite-based measures have three distinct advantages over measurements from ground-based sensors. They provide area-wide averages as opposed to point measurements that may not accurately reflect the pollution levels in the surrounding area; the sensors and techniques for each pollutant are generally consistent across time and space;

[11] I discuss the details of how I process the data in Appendix A.7.

the two pollutants are measured with different sensors and techniques, which provides a useful robustness check.[12]

2.6 Control Variables

2.6.1 Pollution Spillover

Most of the models presented below simply ignore spillover because an overwhelming majority of ground-level air pollution is from local emissions sources. This is especially true for NO_2, which persists in the lower atmosphere for only a few days before breaking down (Jeong et al. 2017). I also employ a series of robustness checks that account for spillover in different ways and find results that are consistent with those shown here. In Appendix A.4, I control for statewide air pollution levels. In Appendix A.6, I include lagged spatial autoregression (SAR) models, which treat spillover as an endogenous phenomenon between a locality and its neighbors.

2.6.2 Economic Output

Annual economic output (i.e., gross regional product—GRP) values are from the Bureau of Economic Analysis and inflation adjusted.

2.6.3 Partisanship

Partisanship can affect how citizens perceive real-world outcomes (Egan and Mullin 2012). I control for this with each locality's average Democratic presidential candidate vote share.

2.6.4 Unmeasured Variables

I account for unmeasured factors like geography and economic composition by including lagged dependent variables (LDV's) in the models, meaning that each model includes the dependent variable (DV) from the previous time period as an explanatory

[12]The $PM_{2.5}$ data are derived from the daily overpass measurements of the MODIS, MISR, and SeaWiFS sensors while the NO_2 data are from the OMI, MetOp-A and MetOp-B sensors.

variable (EV). LDV's effectively control for all otherwise unmeasured determinants of the DV that do not vary substantially from one year to the next. I also check that the results are robust to state and year fixed effects.

2.7 Empirical Model Specification

The basic framework for the statistical models is a system of three equations in which each variable of interest is a function of the other two. Recall that my theoretical expectations are that public concern's effect on air pollution outcomes is mediated through policy effort. In the statistical models, however, air pollution must be expressed as a function of the policy and public concern measures because the former is not a comprehensive measure of all aspects of policy effort. The policy measure reflects CAA enforcement actions, but much of the policy effort scholars have found to be sensitive to public concern does not *explicitly* relate to air pollution and likely takes the form of zoning rules, building permits, and other seemingly unrelated local-level regulatory actions (Huang, Santibanez-Gonzalez, and Song 2018; Monogan, Konisky, and Woods 2016; Pargal et al. 1997; Pinault et al. 2016).

This system of relationships can be expressed as a trio of independent linear models and estimated with OLS. In equations 1, 2, and 3, ΔGRP (gross regional product) is year-on-year local economic output change, the α's are intercepts, the β's are coefficient estimates, the e's are error terms, and the $\hat{\gamma}$'s are vectors of control variables. The models that measure pollution outcomes with $PM_{2.5}$ replace each instance of NO_2 with $PM_{2.5}$ and are otherwise identical (see Appendix A.5).

As stated in the previous section, the equations include lagged dependent variables (LDV's)—that is, they control for the dependent variable's (DV's) value in the previous time period. In essence, the coefficients for the remaining explanatory variables (EV's) reflect the extent to which they explain the DV's *change* from the previous time period. LDV's account for any unmeasured explanatory variables that do not change substantially

from one year to the next.[13]

$$\begin{aligned} Search_{i,t} = \alpha_{1,0} + \beta_{1,1} Search_{i,t\text{-}1} + \beta_{1,2} \Delta NO2_{i,t} + \beta_{1,3} \Delta Enforce_{i,t} \\ + \beta_{1,4} \Delta Statewide\ NO2_{i,t} + \beta_{1,5} \Delta Statewide\ Enforce_{i,t} + \hat{\gamma}_{1,i} + e_{1,i,t} \end{aligned} \tag{2.1}$$

$$\begin{aligned} Enforce_{i,t} = \alpha_{2,0} + \beta_{2,1} Enforce_{i,t\text{-}1} + \beta_{2,2} \Delta Search_{i,t\text{-}1} + \beta_{2,3} \Delta NO2_{i,t\text{-}1} \\ + \beta_{2,4} \Delta Statewide\ Search_{i,t\text{-}1} + \beta_{2,5} \Delta Statewide\ NO2_{i,t\text{-}1} + \hat{\gamma}_{2,i} + e_{2,i,t} \end{aligned} \tag{2.2}$$

$$\begin{aligned} NO2_{i,t} = \alpha_{3,0} + \beta_{3,1} NO2_{i,t\text{-}1} + \beta_{3,2} \Delta GRP_{i,t} + \beta_{3,3} \Delta Search_{i,t\text{-}1} + \beta_{3,4} \Delta Enforce_{i,t\text{-}1} \\ + \beta_{3,5} \Delta Statewide\ Search_{i,t\text{-}1} + \beta_{3,6} \Delta Statewide\ Enforce_{i,t\text{-}1} + \hat{\gamma}_{3,i} + e_{3,i,t} \end{aligned} \tag{2.3}$$

While the equations above are effectively three independent models, they are theorized to be three parts of the same dynamic system. The systemic nature of the theory has empirical implications because dynamic systems can cause modest error correlation between variables of interest (see, for example, Hermida 2015). The result of such error correlation would be to bias the effect estimates toward zero when the relationships in the dynamic have opposite signs (i.e., when variable A's effect on B has the opposite sign of B's effect on A). This is because unmeasured exogenous shocks to public concern or air pollution that persist over time will tend to push their estimated effects on each other in the opposite direction of my theoretical expectations. Assuming the theoretical model is correct, a shock that increases public concern—new medical research on pollution's health consequences, for instance—would cause NO_2 and $PM_{2.5}$ to decrease the following year via responsive policy. If the shock dissipated quickly, it would be like any other source of random error; it would inflate the unexplained variation of the search index, but

[13] In the equations, each coefficient, vector, and error term has one or two subscript numbers. These are simply to indicate that the values are unique (e.g., the error term in Equation 1 is not the same as the error term in Equation 2, and the first β in the first equation is not the same as the second β in that equation).

would not introduce bias. If, however, the shock's effect on concern persisted over multiple years, the search index would remain high even as contemporary NO_2 and $PM_{2.5}$ levels continued to decrease. This would bias pollution severity's estimated effect on the search index in the negative direction. Similarly, a shock to air pollution that persisted would bias the search index's estimated effect on it in the positive direction. If an exogenous event like falling natural gas prices caused a multi-year decrease in pollution levels, those lower levels should decrease public concern as measured by the search index. If, as the search index decreased, the shock continued to reduce pollution levels, the search index's estimated effect on NO_2 and $PM_{2.5}$ would be biased in the positive direction (i.e., toward zero).

I use SEM's to explicitly account for this possible error correlation. Specifications for SEM's are less flexible than for normal regressions, and the error correlation is unlikely to be large enough to present a practical concern (Hermida 2015)—but they allow for comparing the performance of SEM's that specify the error correlation implied by my theory to otherwise identical SEM's that do not. If the theorized dynamic exists, then the effect sizes should be larger and the relative fit better in the SEM's that specify the expected error correlation.

$$\begin{aligned} Search_{i,t\text{-}1} = \alpha_{4,0} + \beta_{4,1} Search_{i,t\text{-}2} + \beta_{4,2} \Delta NO2_{i,t\text{-}1} + \beta_{4,3} NO2_{i,t\text{-}1} \\ + \beta_{4,4} \Delta Enforce_{i,t\text{-}1} + \beta_{4,5} Enforce_{i,t\text{-}1} + \hat{\gamma}_{4,i} + e_{4,i,t\text{-}1} \end{aligned} \tag{2.4}$$

$$\begin{aligned} Enforce_{i,t} = \alpha_{5,0} + \beta_{5,1} Enforce_{i,t\text{-}1} + \beta_{5,2} Search_{i,t\text{-}1} \\ + \beta_{5,3} \Delta NO2_{i,t\text{-}1} + \beta_{5,4} NO2_{i,t\text{-}1} + \hat{\gamma}_{5,i} + e_{5,i,t} \end{aligned} \tag{2.5}$$

$$\begin{aligned} NO2_{i,t} = \alpha_{6,0} + \beta_{6,1} NO2_{i,t\text{-}1} + \beta_{6,2} \Delta GRP_{i,t} + \beta_{6,3} Search_{i,t\text{-}1} \\ + \beta_{6,4} Enforce_{i,t\text{-}1} + \beta_{6,5} \Delta Enforce_{i,t\text{-}1} + \hat{\gamma}_{6,i} + e_{6,i,t} \end{aligned} \tag{2.6}$$

Note that *Search*, *Enforce*, and *NO2* are included as EV's in the SEM equations, and that the *Search* DV is lagged by one year (with its EV's lagged accordingly) so that it

matches the lag of the *Search* EV in the *NO2* (and *Enforce*) equations. This is necessary for estimating error correlation between the DV's.

2.8 Analysis

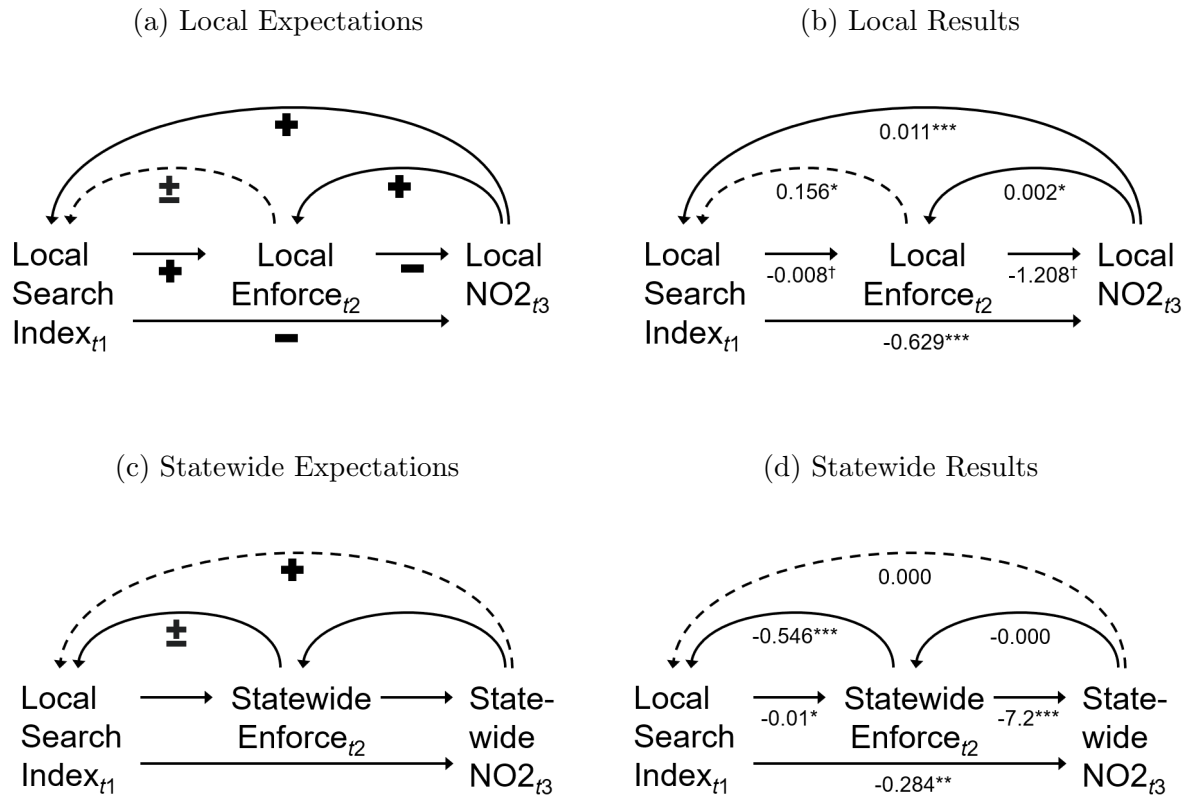
Figures 2.2a and 2.2c summarize the theoretical expectations for the relationships between the DV's in the empirical models.[14] They correspond to figures 2.1b and 2.1c in the theory section. The search index and NO_2 (and $PM_{2.5}$ in Appendix A.5) measure public concern and air pollution. The enforcement variable (*Enforce*) refers to the number CAA enforcement actions, which is a form of policy effort. The unit of analysis is locality-year. The analysis includes all US localities for which data are available (319 CBSA's) from 2010 through 2018. Variables that include the word "statewide" refer to values for the state in which the locality is located.

The effects of enforcement and air pollution on the search index reflect the extent to which the public reacts to information about policy itself and policy's outcomes respectively. Meaningful responsiveness is only possible when citizens have enough information to form coherent opinions and hold government officials accountable. Thus, if policy is indeed meaningfully responsive to local public opinion, citizens must be obtaining some form of relevant information about local matters.

The search index's effect on air pollution reflects the real-world outcomes of policy effort prompted by public concern. It is possible to infer responsive policy's outcomes with this relationship because policy is the only mechanism through which public opinion can significantly affect air pollution on the timescale of this analysis. Popular concern can prompt individual-level behaviors that meaningfully affect air pollution without governmental action, but only on timescales dramatically shorter or longer than this analysis. For example, severe smog often leads people to delay travel plans for days or weeks (Barwick et al. 2019), but such behavioral changes have no net impact on pollution emissions

[14] In Figures 2.2a and 2.2c, the relationships of interest have signs. Models with statewide variables as DV's are not of interest for this study.

Figure 2.2: Theoretical Expectations and Results Summary



Note: The arrows indicate the theorized causal relationships between variables. The dashed arrows represent feedback effects that are predicted to be weak relative to the other feedback effect on the search index. The plus (+) and minus (−) signs indicate expected positive and negative relationships respectively. Plus-minus (±) indicates that the relationship's sign is ambiguous. The coefficients correspond to the Model 3's in Table 2.1 and Table A.4 in the appendix. †p<0.1; *p<0.05; **p<0.01; ***p<0.001.

over the course of an entire year (Welch, Gu, and Kramer 2005). Without policy intervention, public concern only leads to durable changes in individual-level pollution-generating activities (e.g., driving) on timescales of a decade or longer (Tribby et al. 2013).[15]

It is necessary to infer responsiveness from the search index's "direct" effect on air pollution because the enforcement variable is a *partial* measure of total policy effort in a geographical unit. CAA enforcement actions are a major component of governmental air pollution mitigation efforts—but they do not reflect inexplicit policy actions (e.g.,

[15]Environmental activism—which is of course driven by public concern—focuses primarily on pressuring various governing authorities to take some form of action (See Appendix A.8).

zoning, building permits) that scholars have found to be responsive to public sentiment, particularly at the local level (Huang, Santibanez-Gonzalez, and Song 2018; Monogan, Konisky, and Woods 2016; Pargal et al. 1997; Pinault et al. 2016).

2.8.1 Responsiveness

The results strongly suggest that unobserved local-level policy efforts like zoning rules and building permits are responsive to local public concern. If unmeasured aspects of policy are responding to public opinion, a robust negative effect of the search index on NO_2 and $PM_{2.5}$ is what we should see. The same is true of the relative sizes of the search index's effects on NO_2 and $PM_{2.5}$. As shown in Appendix A.5, the searches' negative effect on $PM_{2.5}$ is significantly weaker than it is for NO_2. Given that a higher proportion of NO_2 than $PM_{2.5}$ is from local sources (Chan and Yao 2008; Jiang, Lin, and Lin 2014; Jeong et al. 2017), the search index having a larger effect on NO_2 implies that whatever phenomenon accounts for this estimate is, to a significant degree, local. This result is also evidence against a major unmeasured exogenous event causing a spurious relationship between searches and air pollution. If, for instance, the relationship were due to a dramatic environmental catastrophe that shocked government officials into action and drew public attention nationwide, the searches' estimated effects on NO_2 would likely be smaller because it is more sensitive to local factors than $PM_{2.5}$.

The results indicate that measured policy effort (the *Enforce* variable) is not responsive to year-on-year change of local public concern. If the policy measure were responsive, the search index's effect would be significantly positive.[16] The absence of a robust effect of local search on local enforcement is not surprising given that measured enforcement actions are decided mostly by specialized regulatory entities, which tend to be less sensitive to public concern—and more sensitive to objective problem severity—than other governmental bodies (Mullin 2008).

[16]To be clear, this does not rule out the possibility that CAA enforcement actions are responsive to longer term public opinion trends.

Table 2.1: OLS Regressions with NO2

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	0.559***	0.550***	0.555***
	(0.015)	(0.014)	(0.015)
ΔNO2$_t$	0.011***		0.011***
	(0.002)		(0.003)
ΔEnforce$_t$	0.061		0.156*
	(0.068)		(0.072)
ΔNO2$_t$ (statewide)		0.011***	0.000
		(0.003)	(0.004)
ΔEnforce$_t$ (statewide)		-0.423**	-0.546***
		(0.137)	(0.147)
F Statistic	431.14	437.17	417.24
Resid. Std. Error	3.43	3.41	3.43
R^2	0.89	0.89	0.89
N	2818	2889	2818

(b)

	(1)	(2)	(3)
DV: Enforce$_t$			
Enforce$_{t\text{-}1}$	1.028***	1.027***	1.028***
	(0.005)	(0.005)	(0.005)
ΔSearch$_{t\text{-}1}$	-0.006		-0.008†
	(0.004)		(0.004)
ΔNO2$_{t\text{-}1}$	0.000		0.002*
	(0.001)		(0.001)
ΔSearch$_{t\text{-}1}$ (statewide)		0.003	0.006
		(0.005)	(0.006)
ΔNO2$_{t\text{-}1}$ (statewide)		-0.001	-0.003**
		(0.001)	(0.001)
F Statistic	1102.81	1115.76	1063.42
Resid. Std. Error	0.97	0.96	0.97
R^2	0.95	0.95	0.95
N	3130	3230	3130

(c)

	(1)	(2)	(3)
DV: NO2$_t$			
NO2$_{t\text{-}1}$	0.868***	0.866***	0.865***
	(0.010)	(0.010)	(0.010)
ΔGRP$_t$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
ΔSearch$_{t\text{-}1}$	-0.638***		-0.629***
	(0.138)		(0.142)
ΔEnforce$_{t\text{-}1}$	-2.433***		-1.208†
	(0.607)		(0.643)
ΔSearch$_{t\text{-}1}$ (statewide)		-0.330†	-0.129
		(0.177)	(0.183)
ΔEnforce$_{t\text{-}1}$ (statewide)		-7.895***	-7.200***
		(1.235)	(1.311)
F Statistic	656.44	658.39	639.45
Resid. Std. Error	31.37	31.32	31.20
R^2	0.93	0.93	0.93
N	2818	2818	2818

Note: All models include state fixed effects. The models in subtable *a* control for each locality's Democratic vote share in presidential elections. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

2.8.1.1 Magnitude of Responsiveness

How substantively meaningful is this responsiveness? Based on Table 2.1's Model 3 estimates, a one standard deviation increase in the search index would reduce local NO_2 by 2.8 $\mu g/m^3$ the following year, which is a 1.1 percent change for the average observation.[17] The visibility in daily life of a change of this magnitude would depend on how evenly distributed the change is over the course of a year—in principle, a more even distribution should be less obvious. Assuming a perfectly even distribution and no access to technology (e.g., AQI indexes), annual changes of this size would be perceptible within two to three years; people's self-reported levels of discomfort have been found to shift significantly in response to NO_2 changes as small as 5 $\mu g/m^3$ (Rotko et al. 2002). The effect size also suggests near-term impacts on public health. Annual changes of this magnitude would likely have a small but significant impact on health outcomes within several years. Over longer periods, the health impacts would be profound (see, for example, Jacquemin et al. 2009).

A modest one year effect that becomes substantial over several years is consistent with what one would expect given the types of policy efforts that appear to be responding to local public concern. Indirect efforts like the strategic use of zoning rules and building permits generally cannot force the immediate relocation of emissions sources (e.g., pollution intensive industries, coal-fired power plants), but beyond the very short term, they can have a major role retaining or forcing out existing pollution sources and attracting or repelling new sources to an area.

2.8.1.2 Alternate Explanations for the Responsiveness Relationship

The search index's robust negative effect on air pollution the following year is consistent with substantively meaningful responsiveness. There are, however, competing explanations for this relationship that must be addressed. The most plausible such explanation is the following:

[17] The impact on $PM_{2.5}$ would be 0.1 $\mu g/m^3$, which is a 1.5 percent change for the average observation.

Policy reacting directly to air pollution severity. In this scenario, public concern and policy would correlate because they would be responding to the same signal, and—assuming the government's efforts were effective—searches would be negatively associated with air pollution the following year despite the absence of a causal link.

The relationships between measured enforcement and air pollution account for this possibility. These relationships suggest that measured enforcement is indeed sensitive to local air pollution severity and has a modest effect on pollution severity the following year. However, if authorities were responding almost exclusively to air pollution itself and not public concern, enforcement's effect on NO_2 (and $PM_{2.5}$) should wipe out—or at least substantially reduce—the search index's estimated effect. What we actually see is that the search index remains highly significant even with enforcement included as an EV for pollution.[18]

The remaining possible explanations for the search index's estimated effect on air pollution are highly improbable. These explanations include:

Anomalous weather and reversion to the mean. In principle, anomalous weather increasing (or decreasing) a locality's air pollution for one year and returning to the mean the next year could create the search index's apparent effects on NO_2 and $PM_{2.5}$. To do so, however, the anomalies would need to be long-lived enough to affect a locality's air pollution averaged over exactly one calendar year without being offset by other anomalies. Any weather anomaly that continued beyond one year is an exogenous shock that persists over time. As discussed in the previous section, such shocks bias the relationships *against* my theoretical expectations, and can be accounted for with SEM's (see below). Given that dramatic weather anomalies often persist for multiple years (e.g., drought conditions), the net impact of anomalous weather is unlikely to bias the analysis toward type I error.[19]

[18]Because measured enforcement actions are more sensitive to objective problem severity than most other forms of policy effort, the *Enforce* variable should adequately control for overall policy effort that reacts directly to air pollution.

[19]Consistency between the NO_2 and $PM_{2.5}$ pollution measures is further evidence that the results are

Other unmeasured variables. It is of course impossible to definitively prove there are no other factors causing a spurious relationship between the search index and air pollution, but the possibility is extremely remote. There are no apparent alternative explanations for this relationship that have not already been addressed, and the models explain around 93 percent of NO_2 variation (and 73 percent for $PM_{2.5}$). These high R^2 values are due mostly to the models' LDV's, which account for key pollution determinants like infrastructure, economic composition, and geography that do not change significantly from one year to the next. Explaining nearly all of the pollutant's variation is further evidence that the models are not missing any important variables that could potentially bias the results and cause spurious correlations.

2.8.2 Informing Public Opinion

Meaningful responsiveness requires that the public have enough information to form coherent opinions about whether the government should do more (or less) to mitigate air pollution. The literature has established that the public regularly informs its opinions with statewide (or national) policy information that it almost certainly obtains through the media. Statewide policy's effect on public concern is consistent with this scholarship. Of greater interest for this study is how citizens are obtaining information about local matters.

Public concern reacts to local air pollution (NO_2 and $PM_{2.5}$), and—to a lesser extent—the enforcement actions that occur locally. This indicates that the public is informing its opinions with information about outcomes and (to a smaller degree) policy effort itself.[20] So where is the public getting this information? The policy information is likely obtained through the media. Media is the dominant source of policy information in the literature, and a weak effect of measured policy on public concern is what we would

robust to anomalous weather, for the pollutants are sensitive to different weather phenomenon.

[20]A one standard deviation increase in NO_2 would increase the search index by around 3 percent for the average observation. For Model 3 in Table 2.8, the magnitude of local enforcement's effect on the search index is actually comparable to NO_2's effect but is much noisier and less robust across model specifications.

expect given that local media coverage is sparse but not entirely absent. Local enforcement's positive coefficient is also consistent with media reporting on local matters being sporadic. When there is too little local media to regularly report on routine policy efforts, the few efforts that will tend to attract media coverage are those that are associated with high profile disasters that heighten public concern.

Citizens may also be obtaining some information about local air pollution outcomes through the media. But the evident weakness of local media reporting implies that the public is obtaining the bulk of its information about air pollution outcomes from non-media sources. The most obvious such sources are direct observations from daily life.[21]

2.8.3 Further Evidence of a Dynamic Process

Model 2 in Table 2.2 is a SEM that specifies error correlation between the search index and NO_2 DV's. Model 1 is a SEM that assumes the two DV's are independent but is otherwise identical to Model 2. As discussed in the previous section, any error correlation from the theorized dynamic relationship should bias the relationships of interest towards zero. Thus—if the dynamic exists—ignoring it should lead to smaller estimates for ΔNO_2's effect on the search index and the search index's effect on NO_2. This is exactly what we see in the table. Moreover, the AIC and SABIC values indicate that Model 2, which accounts for the theorized feedback dynamic, has better fit relative to Model 1.

Table 2.2: SEM Results

	(1)	(2)
DV: Search$_{t\text{-}1}$		
Search$_{t\text{-}2}$	0.833***	0.833***
	(0.008)	(0.008)
ΔNO2$_{t\text{-}1}$	0.004	0.008**
	(0.003)	(0.003)
NO2$_{t\text{-}1}$	0.000	0.000

[21] In addition to their own direct observations, citizens may also obtain information regarding other nearby people's direct observations through interpersonal communication.

	(0.001)	(0.001)
ΔEnforce$_{t\text{-}1}$	0.093	0.081
	(0.108)	(0.108)
Enforce$_{t\text{-}1}$	0.066*	0.069*
	(0.031)	(0.031)
DV: NO2$_t$		
NO2$_{t\text{-}1}$	0.803***	0.804***
	(0.006)	(0.006)
ΔGRP$_t$	0.009***	0.009***
	(0.002)	(0.002)
Search$_{t\text{-}1}$	-0.140**	-0.292***
	(0.053)	(0.074)
ΔEnforce$_{t\text{-}1}$	-2.325***	-2.280***
	(0.561)	(0.561)
Enforce$_{t\text{-}1}$	1.137***	1.150***
	(0.174)	(0.174)
Feedback	No	Yes
Akaike (AIC)	86540	86534
Adj. BIC (SABIC)	86786	86783
R^2 (Eqn. 1)	0.72	0.72
R^2 (Eqn. 2)	0.94	0.94
R^2 (Eqn. 3)	0.93	0.93

Note: N = 4679. Estimator: ML. The search equation has year fixed effects. The NO2 equation has state fixed effects. Estimated using 'lavaan' v0.6-2 in R Open 3.5.1. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Chapter 3

China

A large body of scholarship has identified a dynamic relationship between public opinion and policy in settings with strong democratic characteristics, such as electoral mechanisms and independent media. The public in these settings uses policy-related information to form opinions, and policy changes in response to those opinions (Bonafont and Palau 2011; Jennings 2009; Jones, Larsen-Price, and Wilkerson 2009; Jones and Baumgartner 2005, 249–274; Pacheco 2013b; Soroka and Wlezien 2010; Wlezien and Soroka 2012). The extent to which this dynamic exists when democratic features are weak or absent is poorly understood. Responsiveness in nondemocratic settings is common but tends to be narrowly targeted at key constituencies and contingent on situation-specific idiosyncrasies (Cai 2010; Chen, Pan, and Xu 2016; Gandhi and Przeworski 2006; Jiang and Zeng 2019; Jiang, Meng, and Zhang 2019; Li, Liu, and Li 2012; Manion 2014; Malesky and Schuler 2010; Meng, Pan, and Yang 2017; Miller 2015; Truex 2016). The limited nature of this responsiveness raises the question of whether (and to what degree) it yields meaningful real-world benefits for the general public.

Our poor understanding of responsiveness dynamics under nondemocratic circumstances has far-reaching consequences, as many of the settings in which governments' policies are formed and implemented lack strong democratic features. Much of the world's population lives in countries that severely restrict independent media and elections. Even mature democracies often have a dearth of independent media coverage and overlapping jurisdictions that obfuscate accountability at the local level.

To address this imbalance in scholarly focus, we propose a dynamic model of responsiveness that extends to settings where democratic features are weak or absent. A

novel feature of this model is that it brings together public opinion, policy, and policy's real-world outcomes into a single dynamic system. Both the opinion–policy and policy–outcomes relationships have been well studied in isolation, especially in democracies. But neither relationship by itself indicates how much of the policy effort spurred by popular sentiment translates into tangible outcomes. This is true of the policy–outcomes relationship because policy changes can be prompted by both public opinion and objective problem severity, which is an outcome of policy. This is also the case for the opinion–policy relationship because some policies are better implemented and more effective than others. Thus, the literature shows that public opinion drives some policy, and that some policy is effective, but it does not establish how much effective policy is prompted by public opinion. We address this limitation by modeling public opinion, policy, and outcomes as three parts of the same system.

We make a two-fold argument with this model that applies to policy domains with outcomes that are discernible to citizens in their daily lives. (1) We argue that policy responsiveness can be substantively meaningful for the general public—even in nondemocratic settings that restrict citizens' access to policy-related information.[1] For meaningful responsiveness to exist, citizens must have enough reliable information to form coherent opinions. Even the most altruistic, earnestly responsive officials cannot respond to opinions that are logically paradoxical, hopelessly unstable, or simply nonexistent. Government officials also have less incentive to be responsive to citizens who have too little information to hold them accountable for their actions. Even in highly authoritarian settings, citizens often have at least a few tools they can use to hold government officials accountable,[2] but citizens can only use these tools effectively if they are aware of what government officials are doing. (2) We argue that meaningful responsiveness is possible in nondemocratic settings that restrict citizens' access to information is because citizens

[1]By "meaningful" we mean the responsiveness yields outcomes large enough to be perceptible to the general public and affect its welfare.

[2]For instance, citizens can undertake various forms of collective action to punish government officials who act contrary to their desires.

can use direct observations of outcomes to form coherent opinions about whether the government should do more (or less) to address an issue.[3]

This second facet of our argument reflects a key difference between our model and the thermostatic dynamic responsiveness scholarship, which is based on evidence from democratic settings. The thermostatic literature finds that the public reacts to information about increases and decreases in policy action and not the action's real-world outcomes (Jennings 2009; Pacheco 2013b; Soroka and Wlezien 2010, 107–124; Wlezien 1995; Wlezien and Soroka 2012). The logic underlying our model is that the public reacts primarily to the most convenient, seemingly reliable indicator of how well an issue is being addressed by the government. By this reasoning, the literature's findings make sense in liberal systems with robust media coverage; it is sensible for the public in such circumstances to base its preferences for more (or less) policy action in an issue area on its perception of the action itself and not the outcomes—particularly when the outcomes are far removed from everyday life. We argue, however, that when the public lacks credible information on how much the government is doing about an issue (perhaps due to the absence of independent media reporting), people resort to basing their opinions on outcomes they can directly observe.

To test our model, we look at an important issue with objectively measurable outcomes in a nondemocratic political environment: air pollution in Chinese cities. Due to China's virtually nonexistent electoral mechanisms, heavy censorship, and lack of independent media, it represents a most difficult case for our argument—and an ideal case for examining how (if at all) the responsiveness dynamic functions in the absence of democratic features.

Estimating the relationships between public opinion, policy, and outcomes is done using both standard ordinary least squares (OLS) regressions and structural equation models (SEM's), which can account for the error correlation and biased estimates that

[3]Citizens may also use these direct observations to evaluate the performance of governing officials and hold them accountable through whatever mechanisms are available to them (e.g., collective action).

may result from feedback dynamics. To measure air pollution outcomes, we use satellite-derived concentrations of two ubiquitous pollutants: nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$). For public concern, we use the Baidu internet search index,[4] which reflects an issue's salience by indicating the proportion of internet searches related to air pollution in each locality. While this measure is relatively new to the social sciences, scholarship has established that search indexes—including Baidu's (Vaughan and Chen 2015)—are valid measures of issue salience (see Mellon 2013; Oehl, Schaffer, and Bernauer 2017; Swearingen and Ripberger 2014). For policy action, we use the goals municipal governments set out in their annual work reports and the contents of their official newspapers. The reports are a partial measure of overall government action (Wang 2017), and tend to reflect the policy efforts prompted directly by pollution severity. The reports and state media also reflect the policy information that is readily accessible to the public. Our analysis includes all observations for which data are available: 274 prefecture-level cities from 2012 through 2015.

The dependent variables of greatest interest are air pollution outcomes and public opinion. After accounting for non-policy factors (e.g., economic output and emissions from outside sources), year-on-year changes in local air pollution reflect the real-world outcome of policy efforts in a given locality. And after accounting for policy efforts prompted by air pollution severity itself, we can estimate the real-world impact of the policy efforts driven by public opinion. We find that policy is sufficiently responsive to local public opinion to meaningfully affect the public's welfare—a one standard deviation shift in public opinion affects air pollution enough to be perceptible to citizens and affect public health on time scales as short as two to three years.

To address the matter of where the public obtains the information necessary for this responsiveness, we estimate the effects of air pollution, reports, and state media contents on local public opinion. The results indicate that the public reacts to local

[4]Baidu is China's dominant internet search engine. Its internet search index is comparable to Google Trends (Vaughan and Chen 2015).

air pollution severity but mostly ignores available information about governmental policy itself. We speculate that citizens ignore available policy information in this setting because they perceive it to be unreliable.

3.1 Theoretical Model

We propose a dynamic model of responsiveness that incorporates real-world outcomes and extends to nondemocratic settings. The model applies to domains with outcomes that are discernible to citizens in their day-to-day lives.

Regarding our terminology, *policy action* refers to the aggregation of governmental activities that impact an issue in a given location; it is a broad conception of policy (see Kingdon 1995). *Public concern* refers to an issue's salience and the public's preference for the government to do more to address it. In many issue domains—particularly technical domains like environmental matters—public attention to the issue and the degree to which it prefers the government to do more about it go hand in hand (Oehl, Schaffer, and Bernauer 2017).

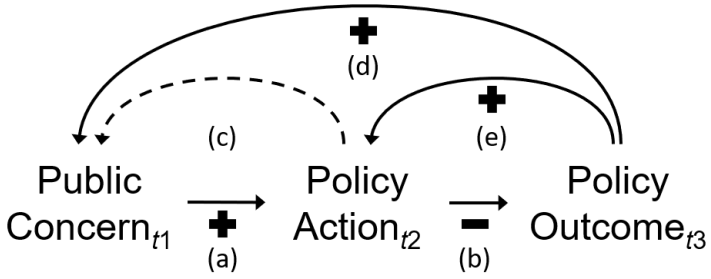
We make a two-fold argument with this model. First, we posit that responsiveness can be substantively meaningful, even in nondemocratic settings.[5] Second, this responsiveness is possible because citizens can form grounded opinions and evaluate the performance of government officials based on the policy outcomes that are discernible in daily life. The first part of this argument can be expressed as two hypotheses, which correspond to relationships a and b respectively in Figure 3.1.

1. Increased (decreased) public concern with an issue increases (decreases) the government's overall level of policy effort addressing it.

2. The additional policy effort prompted by public concern meaningfully mitigates problem severity (i.e., affects outcomes) in that issue domain.

[5]Recall that by *meaningful*, we mean that the additional policy action prompted by public concern yields outcomes large enough to be perceptible to the public and affect its welfare.

Figure 3.1: Theoretical Model Overview



Note: The arrows with plus (+) and minus (−) signs represent theorized positive and negative causal relationships respectively. The dashed arrow signifies that we expect Relationship d to be weak relative to Relationship c. $t1$, $t2$, and $t3$ represent time periods. The arrows pointing from right to left (c, d, and e) represent a variable's effect on another in the following period.

Hypothesis 1 represents policy responsiveness and reflects the findings of the nondemocratic responsiveness literature, which show that nondemocratic governments respond on a limited, ad hoc basis to public sentiment, key constituencies' preferences, and social protests (Cai 2010; Chen, Pan, and Xu 2016; Gandhi and Przeworski 2006; Jiang, Meng, and Zhang 2019; Li, Liu, and Li 2012; Manion 2014; Malesky and Schuler 2010; Meng, Pan, and Yang 2017; Miller 2015; Truex 2016). Hypothesis 2 represents the substantive outcomes of the responsive policy action. This relationship remains poorly understood in the literature. It is well known that policy action can achieve outcomes like mitigating air pollution. The relationship, however, is imperfect. While some policies accomplish their goals, many others fail and can even be counterproductive. Thus, we cannot infer from extant scholarship to what extent the limited policy action prompted by public concern in nondemocratic settings meaningfully affects outcomes.

Our argument's second aspect is that citizens form their opinions with whatever seemingly reliable information is readily available. An important implication of this argument is that policy action's effect on public concern is contingent on the availability of information about policy that the public perceives to be reliable. In other words:

3. Policy has a significant direct effect on public concern *if* citizens have access to information about policy that they perceive to be reliable.

4. Policy outcomes that are discernible in daily life have a robust effect on public concern even when citizens lack credible information about policy itself.

If citizens lack information about policy—or perceive the available information as unreliable—Hypotheses 3 and 4 posit that Relationship d is robust while Relationship c is substantively and statistically weak, perhaps to the point of insignificance (see Figure 3.1). That is, greater (less) problem severity leads to more (less) public concern, but information about policy itself—such as government officials claiming to be doing more to address the issue—have little influence on public sentiment if citizens find the information to be non-credible.

Hypothesis 3 simply reflects extant scholarship. Experiments have shown that citizens use information they believe to be credible to inform their opinions and disregard information they perceive as unreliable (Druckman 2001; Tsfati 2003).[6]

For Hypothesis 4, the scholarly evidence is less clear-cut than it is for hypotheses 1 and 3. It is well known that outcomes affect public opinion, but Hypothesis 4 posits that this effect is *robust*. While some studies have found a strong effect (Egan and Mullin 2012; Kim et al. 2020; Stokes 2016), others have found it to be quite weak (Ansolabehere, Meredith, and Snowberg 2014; Bergquist and Warshaw 2019; Borick and Rabe 2010)—sometimes to the point of being entirely drowned out by the effect of policy itself (Soroka and Wlezien 2010, 107–124). The reason for these divergent findings has not been well explored in the literature. But when taken together, these studies imply that citizens react strongly to outcomes that are discernible in daily life and weakly (or not at all) to those that are not. Studies that aggregate outcomes over large geographic areas (such as nations or American states) find weak or insignificant effects. Studies that measure

[6]There is suggestive evidence that these perceptions are sometimes accurate (Zhang 2018).

outcomes at the local level, where they are most proximate to citizens' daily lives, tend to find much stronger effects.

3.2 Mechanisms

This section discusses the causal mechanisms between our three variables of interest. We pay special attention to those that pertain to our empirical analysis: local air pollution in China.

3.2.1 Policy Action

Responsiveness in nondemocratic systems is driven primarily by government officials' desire to avoid social upheaval (see Cai 2010; Chen, Pan, and Xu 2016; Gandhi and Przeworski 2006; Jiang, Meng, and Zhang 2019; Jiang and Zeng 2019; Li, Liu, and Li 2012; Manion 2014; Malesky and Schuler 2010; Meng, Pan, and Yang 2017; Miller 2015; Truex 2016). Officials can—and frequently do—respond to discontent with repression, but repression is costly and resources are finite. Government officials therefore tend to at least minimally accede to public pressure when the cost of doing so is low relative to the cost of repression. More public concern over an issue increases the number and persistence of citizens who may cause unrest, which increases the cost of repression (see Cai 2010; Chen, Pan, and Xu 2016; Li, Liu, and Li 2012).

In a decentralized political system like China's, authoritarian responsiveness can occur across multiple levels of government. Upper levels may respond to public opinion by pressuring lower level officials to better address issues it perceives to be fueling civil strife. Local level officials may also respond directly to the concerns of their own publics to minimize social tumult that embarrasses them in the eyes of their superiors or even endangers them directly. In China's case, the regime's formal cadre evaluation system facilitates both mechanisms (see Cai 2010; Chen, Pan, and Xu 2016; Li, Liu, and Li 2012; Manion 2014; Meng, Pan, and Yang 2017; Truex 2016). Cadres' promotions are largely based on their annual performance reviews of how well they achieve the various goals

set by the national government, and—to an even greater extent—their apparent success maintaining social stability (Edin 2003). Thus, local level officials face strong incentives to respond to their own publics' concerns enough to avoid unrest and to pursue the priorities set by their superiors, which can themselves be influenced by popular pressure.

There may also be more subtle responsiveness mechanisms that are not based on the threat of social upheaval. Unelected officials in democratic systems are often responsive to public opinion out of a sense of duty and professional responsibility (see Mladenka 1981). This may be true true to some degree in authoritarian systems as well.

Chinese officials have numerous tools at their disposal to monitor public sentiment (Jiang, Meng, and Zhang 2019). The regime regularly conducts interviews and surveys of the public (Brady and Juntao 2009). It has popularly elected (though powerless) advisory bodies that reflect the opinions of some segments of society (Manion 2014; Malesky and Schuler 2010; Truex 2016). Officials take note of the size and subject matter of protests (Cai 2010; Li, Liu, and Li 2012). There are multiple formal channels through which citizens can submit complaints about environmental degradation and other issues at all levels of the political system. Local officials also tend to respond to threats of collective action citizens send through unofficial channels (Chen, Pan, and Xu 2016).

Objective problem severity is likely one of the many indicators government officials use to gauge public concern. Indeed, as we show in Figure 3.1, we expect policy action to be influenced by pollution severity itself to some extent. Pollution severity alone, however, is not a reliable proxy for public concern, as pollution is not public concern's sole determinant. Factors like the public's knowledge of air pollution's health consequences mediate how public opinion reacts to air pollution exposure, and there are other issues that compete for the public's attention (Lo and Leung 2000).

3.2.2 Air Pollution

Air pollution refers to the average concentration of air pollutants at ground level within a given locality. It is a function of policy action. When governments do more to

mitigate air pollution, it will be lower than it would be otherwise. The opposite is also true. It is important to note that while air pollution is a function of policy action, policy action is *not* the primary determinant of a city's air pollution level—at least not in the short to medium term. The main driver of local air pollution is local economic output (Chan and Yao 2008; Jiang, Lin, and Lin 2014). Conceptually, one can think of policy action as a force that pushes air pollution levels above or below a "natural" level that is determined by the local economy.

Policy actions that affect air pollution within a locality come from all levels of government and take a variety of forms; any action that reduces a city's automobile traffic or reliance on coal for electricity, heating, or cooking would reduce pollution emissions to some degree. Many of the most conspicuous actions—such as investments in clean energy—come from the national and provincial governments.

There are also important ways through which local governments affect air pollution levels. Most notably, they often use discretionary regulatory enforcement to pressure polluting firms to relocate to other cities. In a case study based on site visits and interviews with city environmental protection bureau (EPB) officials and senior firm managers in Shangyu, the scholars Zhu, He, and Liu (2014) found that many local firms were relocating to other cities in China because of increasing environmental regulation enforcement by the local government. Large-N studies have corroborated Zhu et al.'s finding that environmental enforcement by local governments is a major factor causing polluting firms to relocate. Pollution-intensive industries are more likely to leave cities which claim to strictly enforce air pollution regulations and are more likely to enter cities that do not (Zheng and Shi 2017; Zhou, Zhu, and He 2017). Foreign direct investment for polluting industries also gravitates towards areas that report having looser anti-pollution enforcement (Zhang and Fu 2008).

Policy action can be conceptualized as having two aspects. One is the pre-implementation stages of policymaking, which include the local political leadership's search for policy solutions, deliberation, and the formation of official policies, goals, and priorities (see Kingdon

1995). The other is the government's implementation efforts. This refers primarily to the activities of the leadership's subordinates—particularly street-level bureaucrats and other low-level officials—that affect local air pollution emissions. Recognizing these two aspects of policy action is important because they may not closely correspond. Policies can be announced by political leaders but never meaningfully carried out, and subordinates can vary the amount of effort they put into mitigating air pollution without explicit directives from the leadership.

In the context of air pollution, implementation efforts are far more sensitive to public concern than official (pre-implementation) policy is. Case studies, interviews with local EPB officials, and quantitative assessments have found that citizens' demands for more air pollution enforcement greatly increase the effort low-level city officials put into mitigating air pollution (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010). Furthermore, in one of the few nation-wide studies on this subject in China, Zheng and Shi (2017) find that official environmental policies and public complaints have independent effects on polluting firms' decisions to leave a province. This pattern of disinvestment by polluting firms suggests that both official policy *and* public pressure have sizable impacts on how well air pollution emissions are regulated in practice. It also strongly implies that much of the public's effect on implementation efforts is direct and not mediated through official policy.

3.2.3 Public Concern

Public concern can react directly to air pollution outcomes because they are directly observable. Even short-term exposure to pollutants like NO_2 and $PM_{2.5}$ causes physical discomfort, and the level of people's self-reported discomfort are sensitive to changes as small as a few percent of the average pollution levels for the observations in our sample (Amundsen, Klæboe, and Fyhri 2008). Surveys also confirm that overwhelming majorities of Chinese residents were aware that local pollution levels were increasing each year long before air pollution monitoring stations existed in most of the country

(e.g., Lo and Leung 2000).

This is not to say that personal discomfort is necessarily the public's sole information source regarding air pollution outcomes—there is a plethora of other potential sources that vary in their reliability and accessibility to the public. For instance, air pollution measurements collected by China's Ministry of Environmental Protection (MEP) have existed for most localities since the 20-aughts and have been easily available since 2013. American diplomatic posts have provided real-time measurements in several major cities since 2008. For those with the motivation to find them, various satellite measures have been available since the early 2000's. Word of mouth and social media also provide ample opportunities for people to share information about air pollution outcomes.

Our model is agnostic as to how much the public relies on any particular information source regarding outcomes. We theorize, however, that the public can filter out unreliable information about outcomes that are directly observable. Consistency between the information from a source and people's direct observations provides a heuristic for evaluating the reliability of that source. Correctly identifying reliable information sources would allow the public to react to air pollution changes too small to be directly perceptible.

3.3 Measuring Variables of Interest

See Appendix B.1 for a table of summary statistics.

3.3.1 Policy Action

Our primary policy action measure is derived from city governments' work reports. Work reports are published by nearly all city governments (as well as the other levels of the political system) within the first two months of each year. The first section of the reports highlights the governments' accomplishments over the previous year, while all

subsequent sections lay out their broad goals for the new year.[7] Our measure is the proportion of each report's prospective sections that discusses topics directly related to air pollution. To calculate this proportion, we identify all paragraphs that include one or more keywords and then divide the combined length of those paragraphs by the length of the report's entire prospective section.[8]

The reports are a *partial* indicator of policy action. They are indicative of the local leadership's policy priorities, which reflect one aspect of policy action; there is qualitative evidence that governments put substantial effort into writing the reports and following through with their stated goals (Wang 2017). However, the reports are not a *comprehensive* indicator of policy action, for they are unlikely to reflect many factors that directly influence implementation efforts. As noted earlier, extant scholarship suggests that much of the public's impact on governmental action is directly on low-level officials' implementation efforts and not mediated through responsive official policy (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010; Zhan, Wing-Hung Lo, and Tang 2014; Zheng and Shi 2017).

As a secondary measure, we use the attention to air pollution in each city's flagship, party-controlled daily newspaper. This measure is the number of articles containing at least one air pollution-related keyword each year (see Appendix B.12). The newspapers are general interest daily publications run by the local governments. While their readership tends to be low, they are an indicator of the attention allocation of a government's propaganda apparatus as a whole. Newspaper coverage of air pollution is essentially coterminous with coverage of the government's actions to address it. Nearly every article on this topic emphasizes how hard the local government is working to mitigate air pollution or the successes of its ongoing efforts.

The reports and newspapers are fundamentally measures of how much govern-

[7] At the start of a new five-year plan, section two focuses exclusively on five-year goals while subsequent sections discuss goals for the year. We exclude the section twos from our analysis in these cases.

[8] See Appendix B.11 for the keywords and how we calculate length.

ments *claim* to be doing about air pollution. As such, they are well suited to test the feedback effect we hypothesize. In an environment with no independent media coverage and heavy censorship, the most viable way for the public to gauge policy action without relying on visible outcomes is to trust what the government says it is doing. These measures allow us to estimate the degree to which public concern reacts to the government's claims relative to visible outcomes.

One cannot reasonably assume that a government's claims are a frank depiction of its efforts. When facing pressure from above or below to do more about air pollution, officials have obvious incentives to exaggerate how much they are doing. The likely bias of these already incomplete measures means that we cannot rely on them to estimate responsiveness. We therefore use changes in air pollution levels to infer government action.

3.3.2 Policy Outcomes

The policy outcome we examine is air pollution severity, which we measure with each city's annual concentrations of two ubiquitous pollutants—NO_2 and $PM_{2.5}$—which are indicative of a city's overall air pollution level. NO_2 and $PM_{2.5}$ typically have correlations of over 0.8 with other major air pollutants, including course particulate matter (PM_{10}), carbon monoxide (CO), and sulfur dioxide (SO_2) (Guo, Wang, and Zhang 2017). In our sample, NO_2 and $PM_{2.5}$ have a correlation of 0.78 with each other.

We calculate each city's annual $PM_{2.5}$ and NO_2 concentrations with daily overpass data from satellites. The $PM_{2.5}$ data are from the Global Annual $PM_{2.5}$ Grids provided by NASA's Socioeconomic Data and Applications Center. Our NO_2 data is from the DOMINO (version 2) and TM4NO2A (version 2.3) datasets provided by the European Space Agency.[9]

These satellite-based measures have three distinct advantages over measurements from ground-based sensors. The data is not subject to manipulation by local officials; it provides area-wide averages as opposed to point measurements that may not accurately

[9]We discuss the details of how we use the data in Appendix B.7.

reflect the pollution levels in the surrounding area; and it provides measurements for two pollutants derived from different satellite-based sensors, which gives us a useful robustness check.[10]

3.3.3 Public Concern

To measure public concern, we use the Baidu internet search index, which reflects the annual proportion of internet searches in the air pollution issue domain in each prefecture-level city. Scholarship has shown that internet searches reflect the overall level of public concern with an issue area (Mellon 2013; Swearingen and Ripberger 2014; Vaughan and Chen 2015). This is especially true for environmental matters, in which the public's concern goes hand in hand with its preference for more policy action (Oehl, Schaffer, and Bernauer 2017).

To be clear, we are **not** claiming that government officials in China depend on internet search indexes to gauge public sentiment. Rather, a search index reflects public concern (Mellon 2013; Oehl, Schaffer, and Bernauer 2017; Swearingen and Ripberger 2014; Vaughan and Chen 2015), which is closely associated with citizens' use of various formal and informal channels to express their opinions to the government. Greater public concern with environmental degradation leads citizens to undertake more online activism, submit more complaints directly to government officials, and sometimes even openly demonstrate (see Dong et al. 2011; Li, Liu, and Li 2012).

Environmental concern is correlated among socioeconomic groups within localities (see, for example, Chen et al. 2011). While more affluent, better educated segments of a city's population are more likely to have convenient internet access, shifts in their level of concern are nevertheless indicative of shifts in the general public's concern in this issue domain.[11]

[10]The $PM_{2.5}$ data are derived from the daily overpass measurements of the MODIS, MISR, and SeaWiFS sensors while the NO_2 data are from the OMI, MetOp-A and MetOp-B sensors.

[11]China's Internet penetration was roughly 34 percent in 2011 and 48 percent in 2015 (China Internet Network Information Center 2011, 2015).

To whatever extent China's pervasive online censorship biases this measure, the result would be to make the key statistical relationships we hypothesize *less* significant. This is because censorship is generally most prevalent in the face of surging public attention. That said, we do not expect a high degree of bias; China's online censorship often (though not always) takes the form of blocked websites as opposed to blocked search terms, meaning that people's pollution-related searches should be reflected in the index regardless of which websites are easily accessible to them.

3.4 Control Variables

3.4.1 Economic Output

Local economic output is the primary determinant of an area's air pollution level. Thus, inferring policy action from shifts in local air pollution levels requires that we control for changes in the area's output. Our measure for each city's output (i.e., gross regional product—GRP) is derived from the data reported in China's official Statistical Yearbook. The Yearbook values are nominal, so to account for regional purchasing power variation, we use the estimates of Brandt and Holz (2006) for price differences between provinces. We then use the official consumer price index of each province to account for inflation.

China's reported economic indicators are famously suspect and there is overwhelming anecdotal evidence that official economic output measures are inflated. Even so, we are confident that official GRP statistics are valid measures for our purposes because this study depends on accurate measurement of *change* in GRP from one year to the next. Satellite images of changes in China's nighttime brightness, which correspond to changes in economic output (Henderson, Storeygard, and Weil 2012), imply that China's reported output statistics are either not greatly inflated or (more likely) inflated consistently over time (Landry, Lü, and Duan 2018). To whatever extent GRP values are not inflated consistently, the error terms in our models will increase, but we see no reason to think that the additional error would bias our results.

3.4.2 Pollution Spillover

Most of the models presented below simply ignore spillover because an overwhelming majority of ground-level air pollution is from local emissions sources (see Appendix B.8 for details). This is especially true for NO_2, which persists in the atmosphere for only a few days before breaking down. We also employ a series of robustness checks that account for spillover in different ways and find results that are consistent with those we show here. Tables 3.3 (and B.4 in the appendix) include models that control for air pollution levels in each city's upwind neighbors. In Appendix B.15, we control for air pollution in each city's adjacent neighbors. In Appendix B.16, we include lagged spatial autoregression (SAR) models, which treat spillover as an endogenous phenomenon between a city and its neighbors.

3.4.3 Top-Down Pressure

We use the attention to air pollution-related matters in the goals set by the provincial and national-level government work reports to control for the effect of top-down pressure on policy action at the local level. For the models presented below, we sum the provincial and national report values with those for the local-level. In Appendix B.9, the reports from each level are separate variables.

3.4.4 Unmeasured Variables

We account for unmeasured factors like geography and economic composition by including lagged dependent variables (LDV's) in our models, meaning that each model includes the dependent variable (DV) from the previous time period as an explanatory variable (EV). LDV's effectively control for all otherwise unmeasured determinants of the DV that do not vary substantially from one year to the next. We also check that our results are robust to province and year fixed effects.

3.5 Empirical Model Specification

The basic framework for our statistical models is a system of three equations in which each variable of interest is a function of the other two. Recall that our theoretical expectations are that essentially all of public concern's effect on air pollution outcomes is mediated through policy action. In our statistical models, however, air pollution must be expressed as a function of our policy *and* public concern measures because we expect that much of the policy action prompted by public concern manifests as increased implementation efforts, which are unlikely to be reflected in formal policy goals.

Also recall that we hypothesize that public concern is dramatically more sensitive to observable outcomes than to available information about policy itself. Public concern must nevertheless be a function of both measured policy and outcomes in our empirical models; testing this hypothesis requires that we compare the effects of these two variables on public concern.

In the equations below, *Search* is the public concern measure (i.e., the internet search index), *Reports* are the government work reports that measure formal policy action, and *NO2* is the air pollution measure. ΔGRP is year-on-year change of local economic output. The α's are intercepts, the β's are coefficient estimates, the e's are error terms, and $\hat{\gamma}$ is a vector of control variables. The models that measure pollution outcomes with $PM_{2.5}$ replace each instance of NO_2 with $PM_{2.5}$ and are otherwise identical.

The EV's of interest are expressed as ΔX_t for the obvious reason that we want to capture the extent to which short-term (year-on-year, in this case) change in the EV affects the DV. We also express the EV's of interest as X_{t-1} to account for the effect of the absolute level of the EV, which is itself a function of changes in previous years.

$$\begin{aligned} Search_{i,t} = \alpha_{1,0} + \beta_{1,1} Search_{i,t\text{-}1} + \beta_{1,2} \Delta NO2_{i,t} + \beta_{1,3} NO2_{i,t\text{-}1} \\ + \beta_{1,4} \Delta Reports_{i,t} + \beta_{1,5} Reports_{i,t\text{-}1} + \hat{\gamma}_{1,i} + e_{1,i,t} \end{aligned} \tag{3.1}$$

$$\begin{aligned} Reports_{i,t} = \alpha_{2,0} + \beta_{2,1} Reports_{i,t\text{-}1} + \beta_{2,2} \Delta NO2_{i,t} + \beta_{2,3} NO2_{i,t\text{-}1} \\ + \beta_{2,4} \Delta Search_{i,t} + \beta_{2,5} Search_{i,t\text{-}1} + \hat{\gamma}_{2,i} + e_{2,i,t} \end{aligned} \tag{3.2}$$

$$NO2_{i,t} = \alpha_{3,0} + \beta_{3,1} NO2_{i,t\text{-}1} + \beta_{3,2} \Delta GRP_{i,t} + \beta_{3,3} \Delta Reports_{i,t} + \beta_{3,4} Reports_{i,t\text{-}1} + \beta_{3,5} \Delta Search_{i,t} + \beta_{3,6} Search_{i,t\text{-}1} + \hat{\gamma}_{3,i} + e_{3,i,t} \quad (3.3)$$

While the equations above are effectively three independent models, we theorize that they are three parts of the same dynamic system. The systemic nature of our theory has empirical implications because dynamic systems can cause modest error correlation between variables of interest (see, for example, Hermida 2015). The result of such error correlation would be to bias the effect estimates toward zero when the relationships in the dynamic have opposite signs (i.e., when variable A's effect on B has the opposite sign of B's effect on A). This is because unmeasured exogenous shocks to public concern or air pollution that persist over time will tend to push their estimated effects on each other in the opposite direction of our theoretical expectations. Consider the following examples. Assuming our theoretical model is correct, a shock that increases public concern—new medical research on pollution's health consequences, for instance—would cause NO_2 and $PM_{2.5}$ to decrease the following year via responsive policy. If the shock dissipated quickly, it would be like any other source of random error; it would inflate the unexplained variation of the search index, but would not introduce bias. If, however, the shock's effect on concern persisted over multiple years, the search index would remain high even as contemporary NO_2 and $PM_{2.5}$ levels continued to decrease. This would bias pollution severity's estimated effect on the search index in the negative direction. Similarly, a shock to air pollution that persisted would bias the search index's estimated effect on it in the positive direction. If an exogenous event like falling natural gas prices caused a multi-year decrease in pollution levels, those lower levels should decrease public concern as measured by the search index. If, as the search index decreased, the shock continued to reduce pollution levels, the search index's estimated effect on NO_2 and $PM_{2.5}$ would be biased in the positive direction (i.e., toward zero).

We use SEM's to explicitly account for this possible error correlation. Specifications for SEM's are less flexible than for normal regressions, and the error correlation

is unlikely to be large enough to present a practical concern (Hermida 2015)—but they allow for comparing the performance of SEM's that specify the error correlation implied by our theory to otherwise identical SEM's that do not. If the theorized dynamic exists, then the effect sizes should be larger and the relative fit better in the SEM's that specify the expected error correlation.

Note that *Search*, *Reports*, and *NO2/PM2.5* are included as EV's in the SEM equations, and that the *Search* DV is lagged by one year (with its EV's lagged accordingly) so that it matches the lag of the *Search* EV in the *NO2/PM2.5* (and *Reports*) equations. This is necessary for estimating error correlation between the DV's.[12]

As pointed out in the previous section, the equations include lagged dependent variables (LDV's)—that is, they control for the dependent variable's (DV's) value in the previous time period. In essence, the coefficients for the remaining explanatory variables (EV's) reflect the extent to which they explain the DV's *change* from the previous time period. LDV's account for any unmeasured explanatory variables that do not change substantially from one year to the next.

$$\begin{aligned} Search_{i,t\text{-}1} = \alpha_{1,0} + \beta_{1,1} Search_{i,t\text{-}2} + \beta_{1,2} \Delta NO2_{i,t\text{-}1} + \beta_{1,3} NO2_{i,t\text{-}1} \\ + \beta_{1,4} Reports_{i,t\text{-}1} + \hat{\gamma}_{1,i} + e_{1,i,t\text{-}1} \end{aligned} \tag{3.4}$$

$$\begin{aligned} Reports_{i,t} = \alpha_{2,0} + \beta_{2,1} Reports_{i,t\text{-}1} + \beta_{2,2} \Delta NO2_{i,t\text{-}1} + \beta_{2,3} NO2_{i,t\text{-}1} \\ + \beta_{2,4} Search\ index_{i,t\text{-}1} + \hat{\gamma}_{2,i} + e_{2,i,t} \end{aligned} \tag{3.5}$$

$$\begin{aligned} NO2_{i,t} = \alpha_{3,0} + \beta_{3,1} NO2_{i,t\text{-}1} + \beta_{3,2} \Delta GRP_{i,t} + \beta_{3,3} Search\ index_{i,t\text{-}1} \\ + \beta_{3,4} Reports_{i,t} + \hat{\gamma}_{3,i} + e_{3,i,t} \end{aligned} \tag{3.6}$$

[12]The *Reports* EV for $NO_2/PM_{2.5}$ is for year t because it has a more robust, stable relationship with the DV than *Reports* at year $t-1$ in this SEM. Because the reports are released at the very beginning of year t and set policy goals government officials work towards over the course of the rest of the year, the "proper" lag for *Reports* in the $NO_2/PM_{2.5}$ equation is ambiguous. The choice of lag for *Reports* does not meaningfully affect our findings.

3.6 Analysis

Figure 3.2a summarizes the theoretical expectations for the relationships between the endogenous variables in the statistical models. Figures 3.2b and 3.2c summarize the results from Table 3.1 below and Table B.2 in the appendix. The search index measures public concern. NO_2 and $PM_{2.5}$ both measure air pollution and the reports are a (partial) measure of policy action. The unit of analysis is locality–year. The analysis includes all Chinese localities for which data are available: 274 localities from 2012 through 2015.

The effects of the reports and NO_2/$PM_{2.5}$ on the search index reflect the extent to which the public reacts to information about policy itself and policy's outcomes respectively. Meaningful responsiveness is only possible when citizens have enough information to form coherent opinions and hold government officials accountable. Thus, if policy is indeed meaningfully responsive to local public opinion, citizens must be obtaining some form of relevant information about local matters.

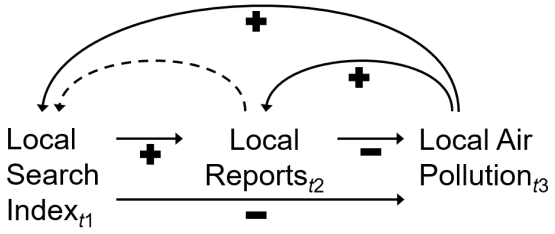
The search index's effects on air pollution (i.e., NO_2 and $PM_{2.5}$) reflect the real-world outcomes of policy action prompted by public concern. It is possible to infer responsive policy's outcomes with these relationships because policy is the only mechanism through which public opinion can significantly affect air pollution on the timescale of this analysis. Popular concern can prompt individual-level behaviors that meaningfully affect air pollution without governmental action, but only on timescales dramatically shorter or longer than this analysis. For example, severe smog often leads people to delay travel plans for days or weeks (Barwick et al. 2019), but such behavioral changes have no net impact on pollution emissions over the course of an entire year. Without policy intervention, public concern only leads to durable changes in individual-level pollution-generating activities (e.g., driving habits) on timescales of a decade or longer (See Appendix B.18).[13]

It is necessary to infer responsiveness from the search index's "direct" effect on air pollution because the reports variable is a *partial* measure of total policy action in a

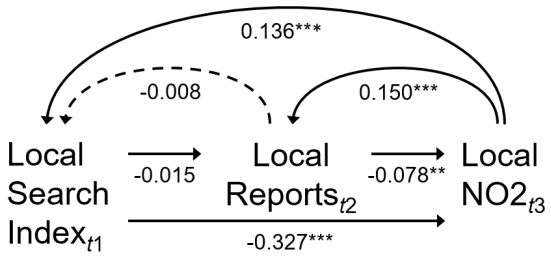
[13]Environmental activism—which is of course driven by public concern—focuses primarily on pressuring various governing authorities to take some form of action (See Appendix B.18).

Figure 3.2: Theoretical Expectations and Results Summary

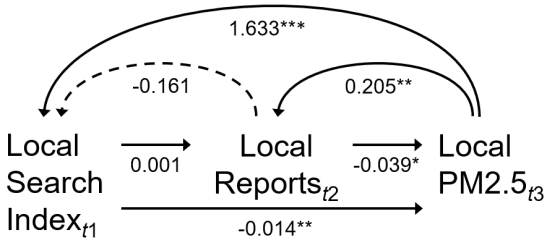
(a) Theoretical Expectations



(b) Results with NO_2



(c) Results with $PM_{2.5}$



Note: The arrows with plus (+) and minus (−) signs represent theorized positive and negative causal relationships respectively. The dashed arrows signify that we expect the relationship to be weak relative to air pollution's effect on the search index. Reports' effects on NO_2 and $PM_{2.5}$ correspond to the Model 2's in 3.1 and B.2 because including both *Reports* and Δ*Reports* as EV's washes out their effects. All other coefficients correspond to the fully specified Model 3's in those tables. †p<0.1; *p<0.05; **p<0.01; ***p<0.001.

geographical unit. They broadly reflect the priorities of government officials, but they are unlikely to reflect much of the effect public concern has on policy implementation efforts, which is where scholarship has found public concern to have the greatest influence on policy action in this issue domain (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010; Zheng and Shi 2017).

3.6.1 Responsiveness

The search index's estimated effect on pollution the following year is consistent with the substantive responsiveness we theorize. If unobserved aspects of policy action—

such as the implementation efforts of low-level officials—are responding to public concern, robust negative effects of the search index on NO_2 and $PM_{2.5}$ is what we should see.

The same is true of the relative sizes of the search index's effects on the two pollutants. A higher proportion of NO_2 than $PM_{2.5}$ is from local sources (Chan and Yao 2008; Jiang, Lin, and Lin 2014; Jeong et al. 2017). The search index having a larger effect on NO_2 therefore implies that whatever phenomenon accounts for this estimate is, to a significant degree, local.[14] This result is consistent with the responsive local policy action we theorize and is evidence against a major unmeasured exogenous event causing a spurious relationship between searches and air pollution. If, for instance, the relationship were due to a dramatic environmental catastrophe that shocked government officials into action and drew public attention nationwide, the searches' estimated effects on NO_2 should not be significantly larger than its effects on $PM_{2.5}$.

3.6.2 Substantive Significance of Responsiveness

How substantively meaningful is this responsiveness? Based on Model 3 in Table 3.1c and Table B.2c, a one standard deviation increase in $\Delta Search$ would reduce local NO_2 by 18.1 $\mu g/m^3$ and local $PM_{2.5}$ by 0.8 $\mu g/m^3$. Based on Model 4 in tables 3.3 and B.4 (see below), a one standard deviation increase in the search index would reduce local NO_2 by 29.4 $\mu g/m^3$ the following year, which is a 4.7 percent change for the average observation. For $PM_{2.5}$, the reduction would be 0.9 $\mu g/m^3$, a 2.4 percent change. China's air pollution levels are so far above what is generally considered to be healthy that no amount of public concern is likely to bring about safe air in the near future.[15] Even so, the effect is sufficient to affect the public in the short term. A reduction in NO_2 and $PM_{2.5}$ levels of this magnitude $\mu g/m^3$ is enough to decrease people's self-reported levels of discomfort (Amundsen, Klæboe, and Fyhri 2008). The effect size also suggests near-

[14] We use a Z-test to determine that the difference is significant.

[15] The average NO_2 and $PM_{2.5}$ levels for the cities in our sample are 627 and 38 $\mu g/m^3$ respectively. For comparison, the World Health Organization considers annual average exposures over 40 $\mu g/m^3$ of NO_2 and 10 $\mu g/m^3$ of $PM_{2.5}$ to be dangerous.

Table 3.1: OLS Regressions with NO2

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	0.966***	0.996***	0.982***
	(0.017)	(0.018)	(0.017)
ΔNO2$_t$		0.052***	0.136***
		(0.014)	(0.016)
NO2$_{t\text{-}1}$	0.023***		0.037***
	(0.003)		(0.003)
ΔReports$_t$		-0.003	-0.008
		(0.011)	(0.013)
Reports$_{t\text{-}1}$	-0.021†		-0.018
	(0.011)		(0.013)
F Statistic	1352.59	1233.64	948.85
Resid. S.E.	46.07	47.60	44.80
R^2	0.85	0.84	0.86
N	977	940	940

(b)

	(1)	(2)	(3)
DV: Reports$_t$			
Reports$_{t\text{-}1}$	0.201***	0.211***	0.201***
	(0.039)	(0.039)	(0.039)
ΔNO2$_{t\text{-}1}$		0.115***	0.150***
		(0.034)	(0.037)
NO2$_{t\text{-}2}$	0.012		0.032*
	(0.013)		(0.014)
ΔSearch$_{t\text{-}1}$		0.031	-0.015
		(0.080)	(0.082)
Search$_{t\text{-}2}$	0.038		0.063
	(0.053)		(0.054)
F Statistic	19.62	20.15	19.18
Resid. S.E.	102.25	101.39	101.07
R^2	0.45	0.45	0.46
N	735	731	731

(c)

	(1)	(2)	(3)
DV: NO2$_t$			
NO2$_{t\text{-}1}$	0.883***	0.886***	0.883***
	(0.013)	(0.014)	(0.013)
ΔGRP$_t$	9.124***	7.519***	11.297***
	(1.665)	(1.658)	(1.689)
ΔSearch$_{t\text{-}1}$		-0.303***	-0.327***
		(0.078)	(0.075)
Search$_{t\text{-}2}$	-0.362***		-0.353***
	(0.052)		(0.050)
ΔReports$_{t\text{-}1}$		-0.078**	-0.042
		(0.027)	(0.036)
Reports$_{t\text{-}2}$	0.072*		0.011
	(0.035)		(0.045)
F Statistic	633.52	607.98	612.51
Resid. S.E.	94.06	91.84	88.61
R^2	0.96	0.96	0.97
N	711	680	680

Note: All models control for each observation's economic output per capita log. The models in subtables *b* and *c* include province fixed effects. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

term impacts on public health. An annual decrease of this magnitude would likely lead to a small but significant reduction in mortality rates within two to three years. Over longer time periods, the health impacts would be profound (He, Fan, and Zhou 2016).

3.6.2.1 Alternate Explanations for the Responsiveness Relationship

The search index's robust negative effects on NO_2 and $PM_{2.5}$ the following year is consistent with substantively meaningful responsiveness. There are, however, competing explanations for these relationships that must be addressed. The most plausible such explanation is the following:

Policy reacting directly to air pollution severity. In this scenario, public concern and policy would correlate because they would be responding to the same signal, and—assuming the government's efforts were effective—searches would be negatively associated with air pollution the following year despite the absence of a causal link.

The relationships between the reports and the air pollution measures account for this possibility. These relationships suggest that policy action is partially driven directly by air pollution severity; the reports are sensitive to both NO_2 and $PM_{2.5}$ and have a significant effect on the more local of the two (NO_2). However, if the government were responding almost exclusively to air pollution itself, the reports' effect on NO_2 and $PM_{2.5}$ should wipe out—or at least substantially reduce—the search index's estimated effect on the pollutants. What we actually see is that the search index remains highly significant even with the reports' measure included as an EV for NO_2 and $PM_{2.5}$. Indeed, the inclusion of the reports measure only modestly reduces the search index's estimated effect.[16]

The remaining possible explanations for the search index's estimated effect on air pollution are highly improbable. These explanations include:

[16]Without *Reports* and Δ*Reports* as EV's for air pollution in the fully specified regressions, *Search* and Δ*Search*'s estimated effects on *NO2* are -0.326 (p=$1.3*10^{-10}$) and -0.318 (p=$4.1*10^{-5}$) respectively. Their effects on *PM2.5* are -0.011 (p=$4.7*10^{-4}$) and -0.020 (p=$2.1*10^{-5}$).

Anomalous weather and reversion to the mean. In principle, anomalous weather increasing (or decreasing) a locality's air pollution for one year and returning to the mean the next year could create the search index's apparent effects on NO_2 and $PM_{2.5}$. To do so, however, the anomalies would need to be long-lived enough to affect a locality's air pollution averaged over exactly one calendar year without being offset by other anomalies. Any weather anomaly that continued beyond one year is an exogenous shock that persists over time. As discussed in the previous section, such shocks bias the relationships *against* our theoretical expectations, and can be accounted for with SEM's (see below). Given that dramatic weather anomalies often persist for multiple years (e.g., drought conditions), the net impact of anomalous weather is unlikely to bias the analysis toward type I error.[17]

Unmeasured policy reacting directly to pollution severity Extant scholarship also rules out the possibility of a spurious relationship from unmeasured forms of policy action reacting directly to air pollution. Interviews and surveys of local EPB officials designed to identify the factors that determine the overall level of their implementation efforts have not found air pollution severity to be significant while they have found local public sentiment to have a major effect (Lo and Fryxell 2005; Zhan, Wing-Hung Lo, and Tang 2014).

Other unmeasured variables. It is of course impossible to definitively prove there are no other factors causing a spurious relationship between the search index and both pollution measures, but the possibility is extremely remote. We are aware of no plausible alternative explanations for this relationship that we have not already addressed, and our models explain around 96 percent of NO_2's and 94 percent of $PM_{2.5}$'s variation. These high R^2 values are due mostly to the models' LDV's because the main determinants of air pollution, like geography and economic composition, do not change significantly from one year to the next. Explaining nearly all of the pollutants' variation implies that

[17]Consistency between the NO_2 and $PM_{2.5}$ pollution measures is further evidence that the results are robust to anomalous weather, for the pollutants are sensitive to different weather phenomena.

our models are not missing any important variables that could potentially bias our results and cause spurious correlations.

3.6.3 Informing Public Opinion

Meaningful responsiveness requires that the public have enough information to form coherent opinions about whether the government should do more (or less) to mitigate air pollution. Thus, the findings above raise the question of where the public is getting this information.

ΔNO_2 and $\Delta PM_{2.5}$ have positive, robust effects on the search index while the reports' effect on searches is insignificant. This set of relationships suggests that public concern reacts to information about air pollution outcomes and mostly ignores available information about policy action itself. The main competing explanation for ΔNO_2 and $\Delta PM_{2.5}$'s apparent effect on the search index is that the public is reacting to information about unmeasured forms of policy action that are negatively correlated with air pollution. After all, such an explanation would be consistent with findings in democratic settings (Soroka and Wlezien 2010, 107–124).

The reports variable helps to rule out this scenario because the reports are fundamentally a measure of how much governments *claim* to be doing about air pollution. In an environment with no independent media and heavy censorship, the government's claims are the only major information source policy action available to the public. The reports' insignificant effect on the search index implies that the public mostly ignores the government's claims.[18]

To further test whether public concern is reacting to the governments' claims, we look at the effect state media coverage of policy action has on the search index. As shown

[18]To be clear, governmental claims are not the public's *only* source of policy information in China. For instance, upper-level policy action receives some coverage in foreign media that motivated individuals can access, and rumors can spread by word of mouth and slip past censors online. Such signals, however, are *extremely* noisy. It is implausible that they could account for the robust estimated effects of $\Delta NO_2/\Delta PM_{2.5}$ and $NO_2/PM_{2.5}$ on the public concern measure.

in Table 3.2, state media's effect is *positive*. Δ*State media* has a large, positive coefficient, and the inclusion of both state media variables modestly reduces the coefficients for ΔNO_2 and NO_2.[19]

Even a cursory look at state media's content and tone makes clear that its coverage of this issue is intended to minimize public concern, so the positive relationship is likely not causal. Rather, the positive sign implies that state authorities allocate media coverage strategically in anticipation of rising public concern; that is, when government officials sense that public concern is beginning to swell, it starts preemptively hyping its actions to mitigate air pollution in an effort to ameliorate public anger.

Taken together, the estimated effects of the reports and state media coverage on the search index provide strong support for our hypothesis that public concern reacts primarily to visible outcomes—and not available information on policy action itself—in nondemocratic settings. The public ignoring the governments' claims about its policy actions implies that citizens perceive the claims as unreliable.

The contrast between the NO_2 and $PM_{2.5}$ model estimates lends further credence to the notion that citizens are reacting to information about outcomes they observe in daily life—not information about policy itself, as is often the case in democracies. Of the two pollutants, ΔNO_2 is the better indicator of changes in policy action within a locality because a higher proportion of NO_2 concentrations are from nearby sources. $PM_{2.5}$, however, is more easily observed by the public. Compared to NO_2, $PM_{2.5}$ exposure tends to cause more physical discomfort (Amundsen, Klæboe, and Fyhri 2008, 7684). $PM_{2.5}$ is also more salient; it is explicitly mentioned on Chinese social media and other forums far more than any other pollutant. Thus, if air pollution's estimated effects on public concern are spurious, and the public is somehow—through unknown mechanisms—accurately perceiving and reacting to shifts in unmeasured policy action, the search index

[19]The significant but relatively small negative coefficient for *State media* is an artifact from a temporal trend that disappears entirely with the inclusion of year fixed effects (while ΔNO_2 and NO_2's effects remain highly significant).

Table 3.2: State Media and Public Concern

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	1.098***	1.051***	1.078***
	(0.019)	(0.016)	(0.018)
ΔNO2$_t$		0.030*	0.073***
		(0.013)	(0.014)
NO2$_{t\text{-}1}$	0.020***		0.023***
	(0.003)		(0.003)
ΔState media$_t$		0.163***	0.115***
		(0.012)	(0.013)
State media$_{t\text{-}1}$	-0.089***		-0.047***
	(0.009)		(0.009)
F Statistic	1341.32	1378.50	1023.27
Resid. S.E.	40.75	40.25	38.42
R^2	0.86	0.86	0.87
N	901	896	896

Note: Models control for economic output per capita (log). Estimator: OLS. The state media measure includes party newspapers at the province and national levels. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

should appear to be more sensitive to ΔNO_2 than $\Delta PM_{2.5}$. What we see, though, is that the public reacts (significantly) more strongly to $\Delta PM_{2.5}$.

3.6.4 Further Evidence of a Dynamic Process

Tables 3.3 (and B.4 in the appendix) compare the variables of interest in models that account for feedback effects to otherwise identical models that ignore them. While models 2 and 4 assume the search index and air pollution have correlated errors, models 1 and 3 assume each equation is an independent regression. The results are supportive of the feedback dynamic we theorize in two key respects. First, the search index's estimated effect on NO_2 (and $PM_{2.5}$) is smaller in the models that ignore feedback, which is consistent with the bias we expect feedback to cause. Second, the models that specify correlated errors from feedback have better relative fit than their counterparts, as can be seen by their lower Akaike Information Criteria (AIC).

Table 3.3: SEM's with NO_2 Pollution Measure

	(1)	(2)	(3)	(4)
DV: Search$_{t\text{-}1}$				
Search$_{t\text{-}2}$	1.080***	1.078***	1.080***	1.079***
	(0.024)	(0.024)	(0.024)	(0.024)
ΔNO2$_{t\text{-}1}$	0.093***	0.113***	0.093***	0.109***
	(0.015)	(0.015)	(0.015)	(0.015)
NO2$_{t\text{-}1}$	0.031***	0.032***	0.031***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
Reports$_{t\text{-}1}$	-0.001	0.002	-0.001	0.001
	(0.014)	(0.014)	(0.014)	(0.014)
DV: Reports$_t$				
Reports$_{t\text{-}1}$	0.206***	0.204***	0.205***	0.205***
	(0.038)	(0.038)	(0.038)	(0.038)
ΔNO2$_{t\text{-}1}$	0.111***	0.112***	0.112***	0.112***
	(0.033)	(0.033)	(0.033)	(0.033)
NO2$_{t\text{-}1}$	0.031*	0.030*	0.030*	0.030*
	(0.014)	(0.014)	(0.014)	(0.014)
Search$_{t\text{-}1}$	0.038	0.038	0.038	0.038
	(0.041)	(0.041)	(0.041)	(0.041)
DV: NO2$_t$				

$NO2_{t\text{-}1}$	0.862***	0.866***	0.752***	0.757***
	(0.013)	(0.012)	(0.015)	(0.015)
Upwind $NO2_t$			0.232***	0.228***
			(0.019)	(0.020)
ΔGRP_t	1.171***	1.072***	0.992***	0.926***
	(0.156)	(0.156)	(0.143)	(0.144)
$Search_{t\text{-}1}$	-0.336***	-0.399***	-0.213***	-0.261***
	(0.038)	(0.045)	(0.036)	(0.043)
$Reports_t$	-0.093**	-0.085**	-0.090**	-0.085**
	(0.033)	(0.032)	(0.030)	(0.030)
Feedback	No	Yes	No	Yes
Akaike (AIC)	25255	25246	25130	25125
Adj. BIC (SABIC)	25351	25344	25228	25225
R^2 (Eqn. 1)	0.82	0.82	0.82	0.82
R^2 (Eqn. 2)	0.46	0.46	0.46	0.46
R^2 (Eqn. 3)	0.96	0.96	0.97	0.97

Note: N = 731. All models control for the log of each observation's per capita economic output. The Reports and NO2 equations include province fixed effects. Estimated using 'lavaan' v0.6-2 in R Open 3.5.1. $^{\dagger}p< 0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

3.7 Discussion

The absence of electoral mechanisms and independent media make China an especially difficult case for our dynamic responsiveness model. Despite the unfavorable setting, however, our model performs quite well. We find that public opinion is informed by directly observable real-world outcomes, and that policy responsiveness yields substantively meaningful real-world outcomes even in the short term. The extent to which these findings generalize across issue areas is a question for future studies, but logic suggests this pattern may extend to issue domains with outcomes that are visible in daily life that citizens perceive as important. Examples of such issues include local school performance, the quality of local infrastructure, and other forms of environmental degradation.

Perhaps our most striking finding is that the public largely ignores the policy-related information that is readily available through official channels and actively disseminated by state media. This finding stands in sharp contrast to what scholars have

consistently found in democracies, where the public generally reacts to policy information that is available through the media or other channels. Why China's public ignores easily accessible policy information in this issue domain is an empirical question that warrants further study. One possibility is that Chinese citizens are simply ignoring information from sources they perceive to be unreliable. It is plausible that citizens judge the reliability of information sources based on how well the information they provide tends to comport with what citizens directly observe in their day-to-day lives.

Chapter 4

Information that Informs the Public

Citizens must have access to reliable policy-related information for governmental responsiveness to be meaningful on a sustained basis. Opinions formed without information are arbitrary and cannot reliably guide policy efforts towards achieving outcomes. Government officials also have less incentive to be responsive to citizens who have too little information to hold them accountable for their actions. Indeed, studies have shown that responsiveness is weaker when the public's access to policy-related information is reduced (see, for example, Gao, Lee, and Murphy 2020; Lax and Phillips 2012; Pacheco 2013b; Rubado and Jennings 2019; Snyder and Strömberg 2010). Opinions based on bad importation undermine responsiveness much like arbitrary opinions formed without information. They are untethered from real-world conditions.

The importance of information reliability for responsiveness raises a key question: can the public distinguish between reliable and unreliable information? This matter is poorly understood in the literature. Experiments have shown that citizens disregard information from sources they perceive as unreliable (Druckman 2001; Ladd 2010; Tsfati 2003), and there is suggestive evidence that these perceptions are often accurate (Druckman 2001; Kim et al. 2020; Zhang 2018). Yet scholarship has also shown that citizens are often bad at identifying biased information (Cain, Loewenstein, and Moore 2005; Durante and Knight 2012; Levendusky 2013), and there are numerous examples in which public sentiment has been distorted by bad information disseminated by the media (Altheide 1997; Bennett 1988; Bennett and Livingston 2018; Jerit and Barabas 2006; Nixon et al. 2015).

I address this question by developing the theoretical model from the previous

chapters to account for why the public uses some available pieces of information to form its opinions but not others. I argue that the public can accurately evaluate information reliability in issue domains with outcomes visible in daily life, as direct observations of real-world outcomes provide citizens with a convenient method to validate information. Associated with this argument, I develop the theoretical model introduced in the previous chapters to more comprehensively address how information accessibility and credibility affect the feedback patterns they find. By this reasoning, citizens are less likely to trust a set of information (the contents of a newspaper, for example) when pieces of that set contradict what they see with their own eyes every day.

4.1 Information

The world is composed of information, also known as data. From the microscopic to the macroscopic, the mundane to the unusual, information is integral to reality. Citizens only ever use a small fraction of this vast quantity of information to form their opinions and make judgments.[1] And of the data within this small fraction, citizens typically depend on some more than others. As expressed in Equation 4.1, the extent to which the public uses a set of information i to form its opinions and make judgments at time t is a function of the information's accessibility and credibility.[2]

$$Info\ usage_{i,t} = f(Accessibility_{i,t}, Credibility_{i,t}) \tag{4.1}$$

4.1.1 Accessibility

Accessibility refers to how easily citizens can obtain and interpret a body of information. In Equation 4.2, the accessibility of information i is a function of the effort required to obtain it (*Obtainment effort*) and interpret it (*Interpretation effort*). Logic dictates that citizens must first obtain any information they use—and that obtained infor-

[1] Or do anything else, for that matter.

[2] As a definitional matter, term *credibility* can be used interchangeably with *perceived reliability*.

mation is only usable to the extent it can be interpreted.[3] Information is highly accessible if the effort needed to obtain and interpret it is minimal. As the effort required increases, the information becomes less accessible.

$$Accessibility_{i,t} = g(Obtainment\ effort_{i,t}, Interpretation\ effort_{i,t}) \tag{4.2}$$

The effort required to obtain and interpret information depends on both the nature of the information itself and citizens' resources for accessing the information. Some information is inherently easy to obtain and understand. This is often true of the information citizens are exposed to in their daily lives, which requires little effort to obtain and can often be understood intuitively, particularly when it concerns matters citizens are familiar with. For instance, driving over potholes while commuting to work informs citizens that roads are in disrepair. The violent, uncomfortable bumps and vibrations that transmit this information to citizens require no effort to receive and understand beyond the act of commuting to work.

Other information must be deliberately sought out and interpreted, which requires effort beyond what citizens would otherwise expend in the course of their daily activities. The accessibility of such information depends on what resources citizens have to facilitate obtaining and interpreting it. These resources can include formal organizations. Independent media companies, for example, specialize in obtaining information and providing it to citizens with sufficient explanation and context to allow for easy interpretation. Interest groups may obtain and disseminate information to promote specific causes. And associations like labor unions may provide and explain relevant information to their members. Resources also include individual-level factors like education and personal experience, as obtaining and understanding new information requires less effort from people who have dealt with similar information in the past.

[3]For the purposes of forming and updating opinions, possessing a body of incomprehensible information is functionally equivalent to simply lacking that information.

The difficulties in obtaining and interpreting information are not necessarily correlated. Information is often easy to obtain but difficult to interpret—particularly in liberal societies, which are characterized by the free flow of information. Large databases of raw governmental budgetary data, for instance, can often be downloaded by anyone with an internet connection. But understanding the data requires additional effort (e.g., summarizing or aggregating the data).

Information may also be easy to understand but difficult to obtain. Internal memos and diplomatic cables, for instance, are often concise and can be easily understood by people with only a passing familiarity with the subject matter. Such information, however, tends to be difficult for most citizens to obtain—it is often classified, and even when it is not classified, obtaining it often requires sorting through archival documents.

4.1.2 Credibility and Reliability

Reliability is an objective quality of information. It is a function of the information's accuracy and completeness (see Equation 4.3). Credibility refers to citizens' perception of information's reliability. Accordingly, credibility is a function of its perceived accuracy and completeness (see Equation 4.4).[4]

$$Reliability_{i,t} = h(Accuracy_{i,t}, Completeness_{i,t}) \tag{4.3}$$

$$Credibility_{i,t} = i(Perceived\ accuracy_{i,t}, Perceived\ completeness_{i,t}) \tag{4.4}$$

Accuracy is simply the degree to which the information accords with objective facts. Completeness is the extent to which it reflects the entirety of information relevant to a given circumstance. Information can be incomplete despite being perfectly accurate. An economic assessment that correctly reports the number of employees hired by just one firm while omitting any mention of mass layoffs economy-wide is accurate, but it is also

[4]The terms *credibility* and *perceived reliability* are interchangeable.

woefully incomplete. Conversly, information can be reasonably complete while only being semi-accurate. An economic assessment based on rough approximations that reflects the overall status of the economy would be an example of this.

4.1.3 Bringing the Equations Together

Equation 4.1 can be combined with equations 4.2 and 4.4 to be re-written as Equation 4.5. The extent to which the public uses a set of information i at time t is a function of the effort required to obtain and interpret the information as well as the public's perception of its accuracy and completeness.

$$\begin{aligned} \textit{Info usage}_{i,t} = j(&\textit{Obtainment effort}_{i,t}, \textit{Interpretation effort}_{i,t}, \\ &\textit{Perceived accuracy}_{i,t}, \textit{Perceived completeness}_{i,t}) \end{aligned} \tag{4.5}$$

4.2 Sources of Information

Citizens have two sources of information. The first is direct observation. The second is media. These sources differ in the types of information they are most effective at providing.

4.2.1 Direct Observations

Direct observations can provide citizens with any information they can see, hear, touch, taste, or smell in their surrounding environment. In the context of governmental policy, citizens may directly observe its real-world outcomes, but not policy itself. Thus, the information citizens can directly observe ($^{Direct}Info$) can be written as Equation 4.6, where *Outcomes* is information about outcomes, α is an intercept, β is a coefficient, and e is an error term that includes all observable information that is not a policy outcome.

$$^{Direct}Info_{i,t} = \alpha_{1,0} + \beta_{1,1} Outcomes_{i,t} + e_{1,i,t} \tag{4.6}$$

Outcomes' visibility—i.e., the degree to which they can be directly observed—

varies by issue area. They can be highly visible by being readily apparent to the entire public on a regular basis (e.g., local environmental, infrastructure, and quality of life issues). They can be partially visible by being apparent to specific segments of the population (e.g., outcomes related to local education are often most evident to citizens with children enrolled in school), or only at specific times (e.g., health care quality is most evident during times of illness or injury). Outcomes can also be practically invisible by being highly abstract and difficult to discern (e.g., financial regulation), or pertain to matters that are far away (e.g., foreign policy).

In most cases, policy efforts themselves cannot be directly observed by the general public.[5] In the course of daily life, most citizens do not come into direct contact with elements of the policy process itself like deliberations among government officials, budgeting, and bureaucratic implementation and enforcement actions.

Of course, some citizens do witness various aspects of governmental policy in their daily lives. After all, the politicians, bureaucrats, and other functionaries who create and carry out policy are themselves citizens. Some citizens who are not government employees may also interface with specific parts of the policy process on a regular basis. Private companies and interest groups, for instance, often employ lobbyists.

In most cases, however, even these citizens can only directly observe a tiny part of a government's total policy activities in a given issue domain. Modern states are large, complex organizations. Their policy efforts in any given issue domain nearly always involve people spread across multiple offices in one or more specialized departments. A low level bureaucrat observes the activities of her office, but not other relevant offices and departments. Even at the uppermost levels of government, senior policymakers cannot directly observe the bureaucratic operations necessary to carry out their directives. No one person can directly observe more than a small fraction of the total policy efforts in a given domain.

[5]The major exceptions are cases in which there is no meaningful distinction between a policy and its immediate outcomes—pensions and other social services citizens directly receive, for example.

4.2.2 Media

Any information the public does not obtain through direct observation must be obtained through one or more media.[6] These media can include the communication methods and organizations conventionally referred to as *mass media*, like newspapers, radio, television, and internet publications. In its broadest sense, media also include fliers and pamphlets and posts on social forums.

Media can convey information about both policy itself and outcomes. The contents of information available through media can thus be expressed as it is in Equation 4.7.

$$^{Media}Info_{i,t} = \alpha_{2,0} + \beta_{2,1}Policy_{i,t\text{-}1} + \beta_{2,2}Outcomes_{i,t\text{-}1} + e_{2,i,t\text{-}1} \tag{4.7}$$

Because policy cannot be directly observed in most cases, media is usually the public's only significant source of policy information. Media may also convey information regarding outcomes.

4.3 Informing Public Opinion

Public opinion is a function of information, which comes from the sources discussed above. Thus, the public's opinion regarding issue i at time t can be expressed as a function of information conveyed through media ($^{Media}Info$) and information that is directly observable ($^{Direct}Info$).

$$Public\ opinion_{i,t} = k(^{Media}Info_{i,t\text{-}1}, ^{Direct}Info_{i,t\text{-}1}) \tag{4.8}$$

The extent to which the public uses a given set of information to form its opinions is moderated by the information's credibility and accessibility. Thus, Equation 4.8 can be expanded like so:

[6] *Media* is literally the plural of *medium*.

$$\begin{aligned} \textit{Public opinion}_{i,t} = l(&{}^{\textit{Media}}\textit{Info}_{i,t\text{-}1} * {}^{\textit{Media}}\textit{Credibility}_{i,t\text{-}1} * {}^{\textit{Media}}\textit{Accessibility}_{i,t\text{-}1}, \\ &{}^{\textit{Direct}}\textit{Info}_{i,t\text{-}1} * {}^{\textit{Direct}}\textit{Credibility}_{i,t\text{-}1} * {}^{\textit{Direct}}\textit{Accessibility}_{i,t\text{-}1}) \end{aligned} \tag{4.9}$$

The pieces of information the public gets from a source do not necessarily all push its opinions in the same direction. Media coverage of outcomes and policy is often closely correlated even though problem severity (i.e., outcomes) and policy typically have opposite effects on public opinion. Media coverage depicting an issue as a severe problem increases public concern (Henry and Gordon 2001; McCreery 2010), while media coverage informing the public that the government is doing more (less) about an issue tends to decrease (increase) the public's preference for the government to take further action and lessens public concern with the issue (Jennings 2009; Pacheco 2013b; Soroka and Wlezien 2010; Wlezien 1995; Wlezien and Soroka 2012).

4.4 Hypotheses

As noted in the introduction of this chapter, the public bases its opinions on information that is accessible and credible (i.e., perceived as reliable) (Druckman 2001; Ladd 2010; Tsfati 2003), but it is unclear from the literature how effectively the public assesses information reliability. On the one hand, scholarship has also shown that citizens are often bad at identifying biased information (Cain, Loewenstein, and Moore 2005; Durante and Knight 2012; Levendusky 2013), and there are numerous examples in which public sentiment has been distorted by bad information disseminated by the media (Altheide 1997; Bennett 1988; Bennett and Livingston 2018; Jerit and Barabas 2006; Nixon et al. 2015).

But on the other hand, public opinion's sensitivity to policy change demonstrates that the public frequently obtains and properly interprets reliable information. While this relationship is likely due in part to aggregation,[7] its robustness in such a wide variety of

[7]Even if many citizens are basing their opinions on inaccurate information, aggregation of individual-level preferences into public opinion may cancel out random errors in individuals' preferences (Page and Shapiro 1992).

settings and issue areas nevertheless implies the public is reasonably good at identifying reliable information in at least some circumstances.

I argue that the public accurately assesses information reliability in issue domains with outcomes that are visible in daily life. The logic underlying this argument is that citizens tend to correctly evaluate information credibility when they can verify it with direct observations from daily life.[8] The implication of this argument is that the public uses reliable information and rejects unreliable information it has access to when it can observe policy outcomes. This can be expressed as the following two hypotheses:

1. Accessible information that is reliable has a robust effect on public opinion.

2. Accessible information that is unreliable does not have a robust effect on public opinion.

Information is seldom perfectly reliable or unreliable. Thus, if hypotheses 1 and 2 are correct, it is also likely that the degree of information's reliability influences how heavily the public weights it when forming opinions.

3. More reliable information has a greater effect on public opinion than less reliable information that is similarly accessible.

4.5 Empirical Strategy

The empirical analysis in this chapter leverages the data from the previous chapters to test the hypotheses. The measures of outcomes and policy in the previous chapters represent different sets of information relevant to air pollution. The reliability of these sets of information varies, as does their accessibility to the public. Thus, comparing the estimated effects of these measures on public concern can provide a test for the hypotheses.

[8]This is not to say this is the *only* way citizens can correctly evaluate information credibility—citizens may, for instance, correctly evaluate information credibility through consistency among disparate information sources.

If hypothesis 1 is correct, the measurements that reflect accessible information that is reliable will have robust effects on the public concern measure. The measures corresponding to accessible, reliable information are those for air pollution in both countries and statewide enforcement in the US.

Note that the US policy measure (Clean Air Act enforcement actions) reflects reliable information about policy itself, but not necessarily the information the public has easy access to. The accessibility of reliable policy presumably depends on how much media coverage it receives, which is not measured. While inconvenient, the lack of a media coverage measure is not a critical problem for testing hypothesis 1—the enforcement measure's statistical effect on public concern indicates the public reacting to reliable information about policy, regardless of its source.

If hypothesis 2 is correct, the measurements that reflect accessible information that is unreliable will not have a robust effect on public concern. The findings in the China chapter strongly imply that the public does not consider state media credible, but do not establish whether state media is objectively unreliable. In the following section I qualitatively assess state media coverage of air pollution and show that it grossly misrepresents reality and is objectively unreliable.

Finally, the effect size of the government work reports' provides suggestive evidence regarding Hypothesis 3. The reports provide something of a middle ground between state media and outcomes in terms of information reliability (Wang 2017).

4.6 China's Information Environment

In China, policy information is highly accessible. At the local level, policy information is even more accessible to the public than in the US. Each level of the political system also has its own daily newspaper dedicated in large part to highlighting its various policy efforts and accomplishments. All levels of the political system, from the national government to the county and prefecture governments, also release annual reports that summarize the the government's previous year's accomplishments and its goals for the

new year. However, this information is generally unreliable (see, for example, Ghanem and Zhang 2014; Rudolph 2016; Wallace 2014).[9]

4.6.1 Reliability

China's environment is characterized by abundant but generally low credibility information about policy. Authorities throughout the government regularly release policy-related information, including outlines of plans and goals (e.g., government work reports) of socioeconomic statistics, and policy outcome indicators (e.g., real-time air pollution data). Authorities also publicize this information and their accomplishments through state media outlets. The authorities responsible for compiling and releasing this information, however, have strong motives to distort it. Local and provincial officials face career incentives to exaggerate how much they are doing to stimulate economic growth and address problems like air pollution (see Landry, Lü, and Duan 2018). Authorities also tend to censor information they view as embarrassing or potentially incendiary to public discontent.

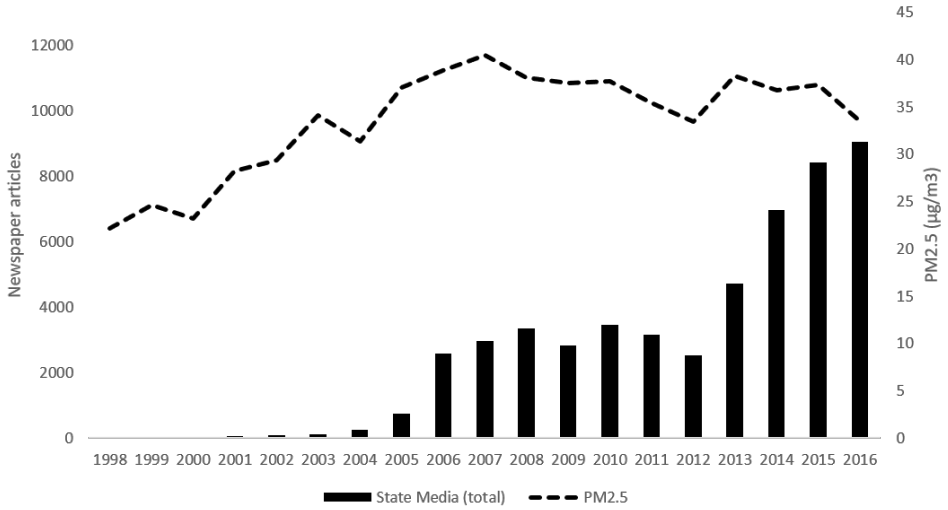
China's official information generally lacks objective credibility. Regarding air pollution, the government has continuously suppressed information about its severity and the threat it poses to public health since the country's economic modernization—and accompanying air pollution problems—began taking off in the 1980's. While the global scientific community has known since the mid-20th century that air pollution exposure is a serious health hazard, the issue was ignored by China's state media until around 2006 (see Figure 4.1).[10]

That media lagged behind objective problem severity is by no means unique to China. In the US, experts had strong evidence that America's high air pollution levels

[9]The unreliability of official information is even recognized within the government itself. As revealed by the 2010 leak of US State Department cables, then vice-premier (and current premier) Li Keqiang openly admitted to American diplomats in 2007 that he distrusted much of the information provided to him by lower levels of government (Unknown 2010).

[10]The World Health Organization considers annual average exposures over 10 $\mu g/m^3$ of $PM_{2.5}$ to be dangerous.

Figure 4.1: Objective Pollution Severity versus State Media Coverage



Note: The keyword totals and $PM_{2.5}$ averages are for the 289 Chinese prefectures in my analysis. Keywords are listed in Appendix B.12.

were harming public health since at least 1948—two decades before air pollution became a salient issue with the American public. Indeed, in terms of air pollution levels and issue salience, pre-2006 China bares a strong resemblance to pre-1968 America (see the next section). In both cases, air pollution was objectively severe but mostly ignored by the public, media, and government for many years.

The key distinction between the two cases is the media's coverage of air pollution once it began to emerge as a salient issue. In the US, the issue's initial salience increase lead to a positive feedback loop between public concern and media coverage. Increased public concern incentivized greater media coverage of the problem. The media coverage then lead to wider dissemination of information about the severity of the problem and its consequences, which increased the public's concern further (McCreery 2010).

In China, by contrast, state media has worked to minimize public concern as air pollution began emerging as a salient issue in the mid to late 20-aughts. The intent of China's media coverage is evident from its tone and substance. Since air pollution began receiving significant media coverage in 2005 and 2006, newspaper articles have consistently downplayed its severity. To the extent they acknowledge air pollution as a

problem at all, they portray it as one that is already being effectively addressed by the government. Most articles highlight some form of government action that has addressed or will address air pollution, such as new investments in monitoring equipment. Typical headlines announce some very general form of action by local or provincial authorities like "Provincial and municipal cooperation to promote air pollution control" (Lanzhou Daily, 2012-06-22) and "Yichuan County strengthens air pollution control in urban areas" (Yanan Daily, 2007-04-17). Articles that discuss air pollution also frequently point out some way in which air quality has improved or how the air quality of the city in which the newspaper is based compares favorably to cities elsewhere.

There has been a noticeable shift in state media's tone since it began covering air pollution in 2005. In the early years, media coverage often took on a tone that was dismissive of air pollution as a serious problem—despite the fact that pollution levels were dangerously high and increasing. A typical headline around then would be something like, "The special [governmental] action has achieved remarkable results" (Ordos Daily, 2005/11/26). State media would occasionally go so far as to explicitly deny air pollution as a problem with a headline like, "The sky is blue, the water is clear, the tree is green" (Gansu Daily, 2005/01/12). From around 2013 to the present day, state media has tended to at least implicitly acknowledge air pollution as a serious problem while still portraying it as one the authorities are effectively handling.

Even as the level of media coverage has increased dramatically over time and taken on a more somber tone since 2013, the coverage has continued to say almost nothing about the specific consequences of air pollution exposure. While state media occasionally runs headlines like "Lung cancer mortality has risen fastest in the past 10 years" (Hebei Daily, 2004-02-23) and "Severe air pollution in Lanzhou threatens the health of more than 2 million residents" (Xinhua Daily Telecom, 2005-03-03), such coverage remains extremely rare.

In addition to spreading misinformation, China's authorities also suppress credible information about air pollution itself that could inflame public concern. Much of this

suppression takes the form of routine censorship. Commercial news outlets and social media platforms are frequently directed to avoid or remove references to mundane cases of elevated air pollution levels and scandals regarding governing authorities shirking their environmental protection duties.[11]

Sometimes information suppression is high-profile and blatant. A prominent example is the Communist Party's reaction to the air pollution measurements from American diplomatic outposts. When the American embassy and consulates in China began measuring and publishing concentrations of individual pollutants like $PM_{2.5}$ in 2008, the Chinese government responded by demanding that the US stop publishing the measurements and blocking access to the information throughout China (Bradsher 2012). Official media—consistent with its strategy of suppressing as much concern-inducing information from the public as possible—continued to be extremely vague when covering air pollution and avoided mentioning specific pollutants. Despite the Communist Party's best efforts, however, public interest in the US measurements eventually proliferated to the point that the authorities mostly gave up censoring the measurements by the early 2010's. Today, fine particulate matter, $PM_{2.5}$, is by far the most salient and generally the most dangerous type of air pollutant in China—but prior to 2009, only one newspaper article in China had ever included the term $PM_{2.5}$. In 2009 and again in 2010, there were exactly two articles that included the term. The number of articles mentioning $PM_{2.5}$ then swelled to 136 in 2011 and 521 in 2012.[12]

The above example highlights a reoccurring pattern in the Chinese government's information suppression efforts. Authorities attempt to block the public's access to concern-inducing information for as long as possible. If and when those efforts fail and the information disseminates to the public, the authorities resort to arguing that the information does not reflect a serious problem—and to the extent that it does, the problem is already being effectively handled by the government.

[11] https://chinadigitaltimes.net/2017/12/2017-propaganda-directives-january-trump-smog-missing-tycoon/

[12] Mentions of other pollutants such as NO_2 and course particulate matter follow similar patters.

Even as authorities tend to (at least tacitly) acknowledge information that is already widely known by the public, they generally continue to suppress related information that is not yet widely known within China. In 2015, for instance, Chinese television host Chai Jing released the self-financed documentary *Under the Dome* about the extreme severity and consequences the country's pollution levels. The documentary attracted overwhelming levels of public attention and was viewed more than 150 million times over several days before being censored (Mufson 2015).

The censorship of the *Under the Dome* documentary is a usefully dramatic example showing that China's government has *actively* suppressed the public's access to information about air pollution. Before 2005, one could reasonably make the case that China's policymakers and media outlets were simply responding to public demand by ignoring air pollution much like the US government and media did prior to 1968. China's public was not concerned with air pollution back then (Lo and Leung 2000), and the same was true of government officials and the media coverage they controlled. However, the overwhelming public interest in *Under the Dome* and Chinese authorities banning it just days after its release illustrates that the government has continued to block information about air pollution despite public interest in the issue.

4.6.2 Credibility

The public's perception of information credibility in China is poorly understood in the literature. Despite the low objective credibility of officially sanctioned information, large majorities of Chinese survey respondents consistently express extraordinarily high levels of trust in their government and official media (e.g., Edelman 2018). Taken at face value, this would seem to imply that the public is naive. However, a more thorough consideration of available survey-based studies and abundant anecdotal evidence strongly suggests that China's public correctly evaluates signal credibility in issue domains with directly observable outcomes. This is likely because direct observations provide the public with a trustworthy (though noisy) signal against which it can judge the reliability of other,

often more precise signals.

The real-world actions of many Chinese citizens suggest substantial distrust of official claims. A prominent example of this distrust is the fallout from the 2008 milk crisis, in which melamine contamination of milk led to the hospitalization of tens of thousands of infants and multiple deaths. Despite the government's insistence that it has remedied the problem, many Chinese with the means to do so still buy baby formula abroad because they do not trust the safety of the domestic supply (see, for example, Chan 2018).

The Chinese public is also susceptible to the spread of rumors, which empirical analysis and simulations have shown to be indicative of low perceived credibility of official information sources (Paek and Hove 2019; Zhang et al. 2014). Rumors regularly spread in the wake of major disasters and spark panic behavior such as panic buying, mass exoduses, and fear and harassment of people from afflicted areas. There are many examples of such rumor-fueled panics in China, such as the 2003 SARS epidemic, the 2005 Jilin chemical plant explosions, the 2009 swine flu epidemic, the 2011 Fukushima Daiichi Nuclear Power Plant disaster, and the ongoing coronavirus epidemic which began in late 2019.

Panics and rumors are not unique to China or authoritarian systems more generally, but their frequency and prominence in China is remarkable given the country's heavy-handed controls over all forms of media and telecommunication, which are designed to prevent the spread of rumors and all other unauthorized information. Because censorship is especially pervasive in China, one would expect the country to have substantially less rumor-induced panic than elsewhere—*if* the Chinese public perceived officially sanctioned information to be at least as credible as the publics in more liberal societies do. What we actually see, however, is that—subjectively at least—rumor-induced panic is as virulent as it is in liberal societies, if not more so. As an example, the 2011 disaster at the Fukushima Daiichi Nuclear Power Plant in Japan caused a torrent of rumors to wash over eastern Asia regarding radiation exposure, despite there being little danger outside the immediate area of the disaster. As a result, panic buying of potassium iodide tablets

occurred across the region and even to some extent in the western US. Panic buying in China was also very severe, and even included the mass buying of salt by residents who wrongly believed ingesting it would protect against radiation exposure. The magnitude of the panic buying of salt caused a ten-fold price increase in several major Chinese cities (Unknown 2011). There is no evidence of panic buying at an equivalent magnitude in the nearby democracies of South Korea, Japan, and Taiwan.

Even outside of major crises, expressions of distrust are commonplace on Chinese social media. It is common for people echoing the Communist Party's rhetoric on social media to be accused by other commenters of being paid government shills. Even posts from official government accounts are sometimes openly accused by commentors—who are required to use their real names to log onto social media platforms in China—of being untrustworthy. For example, on April 1, 2016, state media organ Xinhua declared on the popular Weibo microblog website that "the West's so-called 'April Fools' day" was inconsistent with "the core values of socialism" and admonished citizens to not spread unsanctioned information (i.e., "rumors"). The post attracted wide-spread derision before its comments section was closed, with many comments being some variation of "for state-media, every day is April Fools day" (see China Digital Times 2016).

How can these real-world behaviors be reconciled with surveys that consistently find extraordinarily high levels of trust in their government and official media? Before discussing survey-based findings, it should also be noted that *trust* is a multifaceted concept (see, for example, Kohring and Matthes 2007) and may not be synonymous with perceived honesty. Trusting an institution does not inherently entail believing what the institution says is credible. People may believe that authorities regularly lie to the public but trust that they do so for good reasons (e.g., avoiding mass panic). People may even recognize that authorities regularly lie, believe that they it is wrong for them to lie, but still generally trust their judgment for governing. After all, despite the Communist Party's many conspicuous and often tragic governing failures, living standards have improved dramatically for much of the country's population over the past several decades.

Even taking the survey results at face value, the trust expressed by China's public is specific to the *central* government; when asked about local authorities, citizens report dramatically less trust (Chen 2017; Li 2004; Wu and Wilkes 2018). If—as I theorize—people use observations from their day-to-day lives to evaluate the credibility of other signals, this hierarchical pattern of trust is consistent with what one would expect. Due to their proximity to the public, lies and misconduct by local officials (or its immediate aftermath) are often directly observable (e.g., poorly regulated factories exploding). It therefore makes sense that the public has learned to distrust local government. The national-level authorities in Beijing, on the other hand, are more distant from most of the public and their actions impact people's day-to-day lives much less directly, which makes any lies or misconduct they may be guilty of difficult to discern from direct observations alone.[13]

4.7 US Information Environment

In the US, reliable policy information about national and state-level government is accessible through the media. The quality of media content is uneven (Druckman 2005), but reliable information is nevertheless plentiful for the national and (to a lesser extent) state levels (Lyons, Jaeger, and Wolak 2013; Soroka and Wlezien 2019).

4.7.1 Reliability

In the air pollution issue area, the information environment has been very much like that of other salient domains. The issue receives significant media coverage in the US, which (for the most part) reasonably depicts real-world circumstances (McCreery 2010). The public also reacts to signals in the media regarding air pollution (and the environment more generally) as it does in other major issue domains (Downs 1972; Henry and Gordon 2001; Wlezien 1995). There is no apparent indication that it considers the signals available

[13]National-level authorities also take advantage of this structure by scapegoating local officials for high-profile governance failures.

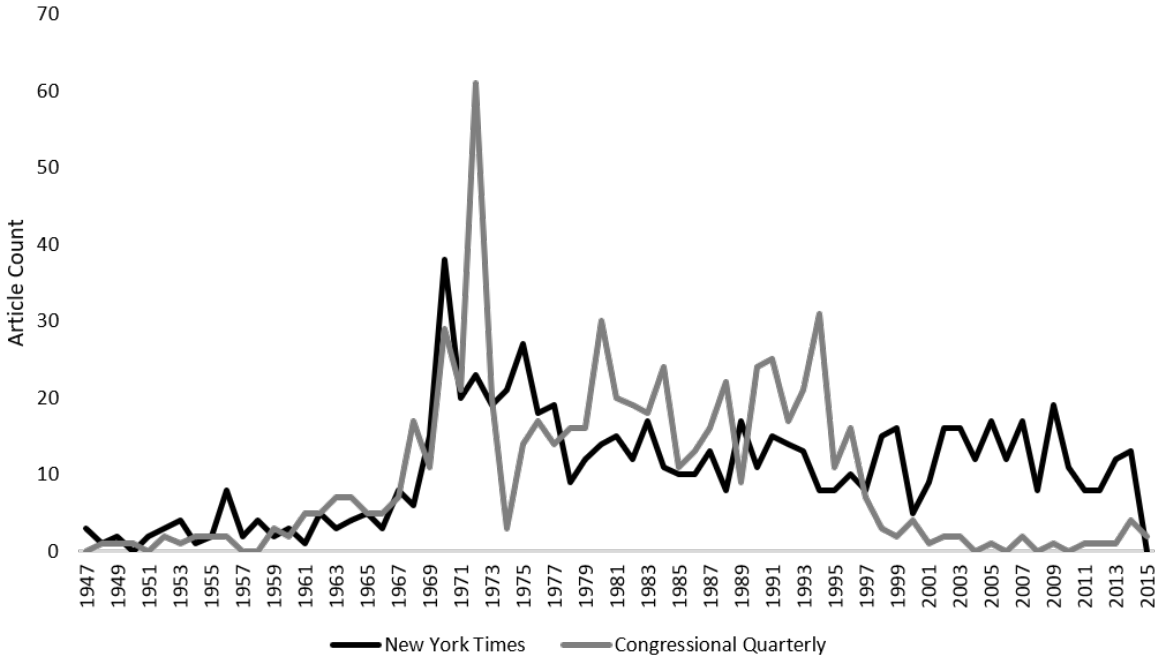
through media reporting to be any less credible in this issue domain than others.

The air pollution issue has been relatively stable in the US since the late-1970's. Air pollution severity, media coverage, and public concern with the issue have fluctuated from year to year while following a gradual long term decline. Over the same time period, budget appropriations related to pollution control and abatement have osculated at semi-regular intervals with few drastic year-on-year changes.

This issue area has not always been so stable. There was a substantial lag between air pollution reaching objectively hazardous levels and becoming a salient issue. While there was little in the way of systematic measurement before the 1970's, air pollution posed a serious threat to public health in much of the US by the early to mid 20th century. Air pollution had long been suspected of causing health problems, and the scientific community began to empirically establish the link in the late 1940's. Yet, two decades passed between strong evidence emerging that air pollution was a severe problem and the issue becoming salient in the late 1960's. Despite the US's liberal, pluralist media environment, the period from the 1940's through the 1960's was characterized by low information accessibility in this domain—that is, information showing that air pollution was a serious problem existed during this time, but was ignored by the media and government and therefore not accessible to the public.

In the late 1960's, information related to air pollution became easily accessible to the general population. As can be seen in Figure 4.2, media coverage exploded. Broadly speaking, this coverage was objectively credible. The media accurately portrayed air pollution as a serious problem that threatened public health. The information was also generally perceived as credible by the public. The dramatic increase in media coverage of the issue fueled public concern (McCreery 2010). The increased public concern also quickly led to increased government efforts to mitigate air pollution. As can be seen in Figure 4.3, the legislative activity related to environmental protection swelled in the late 1960's and early 1970's.

Figure 4.2: Media Coverage of Environmental Issues



4.7.2 Credibility

In surveys, US citizens tend to express far more distrust of mass media than their Chinese counterparts (see Edelman 2018). Even so, the media is a critical mechanism for informing the public (Barabas and Jerit 2009; Eveland 2002; Fraile and Iyengar 2014; Hiaeshutter-Rice, Soroka, and Wlezien 2019; Jerit, Barabas, and Bolsen 2006; Williams and Schoonvelde 2018). Despite apparent distrust in "the media" in the aggregate, most citizens clearly trust specific portions of the media enough to depend on the information they provide.

4.8 Analysis

Tables 4.1 and 4.2 display the results from the search index models from the previous chapters. As pointed out above, local air pollution is reliable and accessible to the public. Its robust effect on the public concern measure in both countries is consistent with Hypothesis 1. The same is true for statewide enforcement effort in the US.

Table 4.1: Public Concern in US Localities

	(1)	(2)	(3)
DV: Search Index$_t$			
Search$_{t\text{-}1}$	0.559***	0.550***	0.555***
	(0.015)	(0.014)	(0.015)
ΔNO2$_t$	0.011***		0.011***
	(0.002)		(0.003)
ΔEnforce$_t$	0.061		0.156*
	(0.068)		(0.072)
ΔNO2$_t$ (statewide)		0.011***	0.000
		(0.003)	(0.004)
ΔEnforce$_t$ (statewide)		-0.423**	-0.546***
		(0.137)	(0.147)
Dem. Vote Prop.$_t$	-1.797*	-1.926**	-1.849*
	(0.753)	(0.745)	(0.752)
F Statistic	431.14	437.17	417.24
Resid. Std. Error	3.43	3.41	3.43
R^2	0.89	0.89	0.89
N	2818	2889	2818

Note: Estimator: OLS. State fixed effects included. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 4.2: Public Concern and Government Work Reports in Chinese Localities

	(1)	(2)	(3)
DV: Search index$_t$			
Search index$_{t\text{-}1}$	0.887***	0.855***	0.869***
	(0.022)	(0.019)	(0.021)
NO2$_{t\text{-}1}$	0.094***		0.169***
	(0.006)		(0.006)
ΔNO2$_t$		0.077***	0.112***
		(0.017)	(0.018)
State media$_{t\text{-}1}$ (prov+local)	-0.151***		-0.041
	(0.027)		(0.033)
ΔState media$_t$ (prov+local)		0.131***	0.110***
		(0.034)	(0.039)
Reports$_{t\text{-}1}$ (prov+local)	-0.007		-0.050*
	(14.944)		(19.303)
ΔReports$_t$ (prov+local)		-0.021	-0.042*
		(11.647)	(14.890)
GRP percap log$_t$	0.102***	0.122***	0.096***
	(3.874)	(3.815)	(3.809)
F Statistic	164.02	165.88	162.04
Resid. Std. Error	43.59	43.11	41.62
R^2	0.85	0.86	0.87
N	790	755	755

Note: Estimator: OLS. Province fixed effects are included. Coefficients are standardized. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Figure 4.3: US Environmental Bills Introduced by Congress

State media coverage is designed to reduce public concern with air pollution. The absence of a negative coefficient for Chinese state media is consistent with Hypothesis 2. The China chapter demonstrates that the positive significant coefficient for state media is due to its coverage anticipating public concern, not public opinion reacting to coverage.

The results also suggest that the public weights the information it uses based on the degree of its reliability (Hypotheses 3). The reports are likely less reliable than air pollution outcomes, but more reliable than state media. Thus, its weak effect on public opinion is in line with Hypotheses 3.

Local policy (*Enforcement)* does not have a significant effect on public opinion, despite the measure reflecting information. Given the weakness of local media coverage in the US, the absence of a robust effect suggests that the public does not have easy access to this information, not a deliberate choice to ignore it.

While US media coverage is not measured, there is nevertheless indirect evidence that the accessibility of policy information is heavily influenced by the abundance of media

coverage. Table 4.3 interacts the proportion of each state's residents employed in media with statewide enforcement. The interaction term indicates that as more people work in media, the effect of statewide enforcement becomes larger. This is what one would expect to see if the accessibility of policy information depends on the level of media coverage.

The media employee variable is the total employment by state-year in publishing (NAICS industry code 511) divided by the total number of employed people in the state. The NAICS 511 classification refers to non-Internet publishing industries The classification excludes Internet publishing and jobs related to the physical manufacturing of print media (e.g., book binding printing). This measurement is from the Bureau of Economic Analysis (BEA).

Table 4.3: US Localities with Statewide Media Proxy

	(1)	(2)
DV: Search$_t$		
Search$_{t\text{-}1}$	0.948***	0.948***
	(0.007)	(0.007)
ΔNO2$_t$	0.012***	0.012***
	(0.003)	(0.003)
ΔEnforce$_t$	0.116	0.124
	(0.082)	(0.082)
ΔNO2$_t$ (statewide)	-0.003	-0.003
	(0.004)	(0.004)
ΔEnforce$_t$ (statewide)	-0.327*	1.065†
	(0.146)	(0.575)
Media Employ (statewide)$_t$	37.439	39.949
	(29.732)	(29.721)
Dem. Vote Prop.$_t$	1.514*	1.414*
	(0.691)	(0.691)
M. Employ:Enforce (statewide)$_t$		-344.088*
		(137.404)
F Statistic	2357.78	2067.71
Resid. Std. Error	3.92	3.92
R^2	0.85	0.85
N	2818	2818

Note: Estimator: OLS. State fixed effects not included. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Appendices

Appendix A

Supplemental Information for Chapter 2

A.1 Summary Statistics

Table A.1: Summary Statistics

	Mean	S.D.	Min	Max
Search (6 terms)$_t$	13.42125	8.570568	0	61.75
Search (6 terms)$_{t\text{-}1}$	13.54951	8.181953	0	58.83333
Search (5 terms)$_t$	18.34895	11.55776	0	81.75
Search (5 terms)$_{t\text{-}1}$	19.28071	11.42113	0	77.66667
NO2$_t$	254.8604	122.0554	19.72583	993.6047
NO2$_{t\text{-}1}$	259.7608	130.0932	19.72583	1090.651
PM2.5$_t$	7.658345	2.376851	1.139318	16.39213
PM2.5$_{t\text{-}1}$	7.882776	2.477994	0.9180887	16.39213
ΔNO2$_t$	-4.900423	35.01619	-217.497	188.6296
ΔNO2$_{t\text{-}1}$	-6.622212	37.37517	-222.7452	188.6296
ΔNO2 (statewide)$_t$	-4.199219	24.36292	-96.56178	75.25637
ΔNO2 (statewide)$_{t\text{-}1}$	-6.176621	26.55953	-152.0546	75.25637
ΔPM2.5$_t$	-0.2244304	1.26376	-4.982957	5.132811
ΔPM2.5$_{t\text{-}1}$	-0.08542054	1.179103	-4.982957	5.132811
ΔPM2.5 (statewide)$_t$	-0.2263526	1.141958	-4.258056	2.713528
ΔPM2.5 (statewide)$_{t\text{-}1}$	-0.08800817	1.042167	-4.258056	2.713528
Enforce$_t$	0.5822171	3.019115	-0.8488506	55.75604
Enforce$_{t\text{-}1}$	0.5809895	3.031916	-0.4525793	55.75604
Enforce (statewide)$_t$	0.9675231	1.955453	-0.6971679	7.765754
Enforce (statewide)$_{t\text{-}1}$	0.960239	1.923436	-0.6987592	7.765754
ΔEnforce$_t$	0.001227588	0.7714145	-13.39603	12.54947
ΔEnforce$_{t\text{-}1}$	-0.009743018	0.832896	-13.39603	19.91786
ΔEnforce (statewide)$_t$	0.007284082	0.5304317	-1.825608	3.048172
ΔEnforce (statewide)$_{t\text{-}1}$	0.001668211	0.5426521	-1.825608	3.048172
ΔGRP$_t$	34.8879	264.227	-4006.127	5713.728
Dem vote share$_t$	0.4263156	0.1204684	0.115477	0.8038521

The ΔGRP values are divided by 10 for the SEM's. The variable's summary statistics are transformed accordingly.

A.2 OLS Models

Table A.2: OLS Regressions with NO2 (5 search terms)

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	0.590***	0.576***	0.581***
	(0.013)	(0.013)	(0.013)
ΔNO2$_t$	0.011***		0.008*
	(0.002)		(0.003)
ΔEnforce$_t$	0.058		0.189*
	(0.080)		(0.085)
ΔNO2$_t$ (statewide)		0.013***	0.005
		(0.003)	(0.005)
ΔEnforce$_t$ (statewide)		-0.589***	-0.735***
		(0.162)	(0.174)
F Statistic	557.83	567.80	541.09
Resid. Std. Error	4.06	4.03	4.04
R^2	0.91	0.91	0.91
N	2818	2889	2818

(b)

	(1)	(2)	(3)
DV: Enforce$_t$			
Enforce$_{t\text{-}1}$	1.028***	1.027***	1.028***
	(0.005)	(0.004)	(0.005)
ΔSearch$_{t\text{-}1}$	-0.005		-0.006
	(0.003)		(0.003)
ΔNO2$_{t\text{-}1}$	0.000		0.002*
	(0.001)		(0.001)
ΔSearch$_{t\text{-}1}$ (statewide)		0.010*	0.011**
		(0.004)	(0.004)
ΔNO2$_{t\text{-}1}$ (statewide)		-0.001	-0.003**
		(0.001)	(0.001)
F Statistic	1102.63	1118.03	1065.52
Resid. Std. Error	0.97	0.96	0.97
R^2	0.95	0.95	0.95
N	3130	3230	3130

(c)

	(1)	(2)	(3)
DV: NO2$_t$			
NO2$_{t\text{-}1}$	0.867***	0.866***	0.865***
	(0.010)	(0.010)	(0.010)
ΔGRP$_t$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
ΔSearch$_{t\text{-}1}$	-0.244*		-0.266*
	(0.111)		(0.111)
ΔEnforce$_{t\text{-}1}$	-2.512***		-1.291*
	(0.609)		(0.645)
ΔSearch$_{t\text{-}1}$ (statewide)		-0.193	-0.174
		(0.138)	(0.138)
ΔEnforce$_{t\text{-}1}$ (statewide)		-7.825***	-7.074***
F Statistic	652.26	658.00	635.67
Resid. Std. Error	31.46	31.33	31.29
R^2	0.92	0.93	0.93
N	2818	2818	2818

Note: All models include state fixed effects. The models in subtable *a* control for each locality's average Democratic vote share in presidential elections for this time period. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

A.3 Statewide Models

Table A.3: OLS Regressions with NO2 (6 search terms)

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t-1}$	0.559***	0.550***	0.555***
	(0.015)	(0.014)	(0.015)
ΔNO2$_t$	0.011***		0.011***
	(0.002)		(0.003)
ΔEnforce$_t$	0.061		0.156*
	(0.068)		(0.072)
ΔNO2$_t$ (statewide)		0.011***	0.000
		(0.003)	(0.004)
ΔEnforce$_t$ (statewide)		-0.423**	-0.546***
		(0.137)	(0.147)
F Statistic	431.14	437.17	417.24
Resid. Std. Error	3.43	3.41	3.43
R^2	0.89	0.89	0.89
N	2818	2889	2818

(b)

	(1)	(2)	(3)
DV: Enforce$_t$			
Enforce$_{t-1}$	1.028***	1.027***	1.028***
	(0.005)	(0.005)	(0.005)
ΔSearch$_{t-1}$	-0.006		-0.008†
	(0.004)		(0.004)
ΔNO2$_{t-1}$	0.000		0.002*
	(0.001)		(0.001)
ΔSearch$_{t-1}$ (statewide)		0.003	0.006
		(0.005)	(0.006)
ΔNO2$_{t-1}$ (statewide)		-0.001	-0.003**
		(0.001)	(0.001)
F Statistic	1102.81	1115.76	1063.42
Resid. Std. Error	0.97	0.96	0.97
R^2	0.95	0.95	0.95
N	3130	3230	3130

(c)

	(1)	(2)	(3)
DV: NO2$_t$			
NO2$_{t-1}$	0.868***	0.866***	0.865***
	(0.010)	(0.010)	(0.010)
ΔGRP$_t$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
ΔSearch$_{t-1}$	-0.638***		-0.629***
	(0.138)		(0.142)
ΔEnforce$_{t-1}$	-2.433***		-1.208†
	(0.607)		(0.643)
ΔSearch$_{t-1}$ (statewide)		-0.330†	-0.129
		(0.177)	(0.183)
ΔEnforce$_{t-1}$ (statewide)		-7.895***	-7.200***
		(1.235)	(1.311)
F Statistic	656.44	658.39	639.45
Resid. Std. Error	31.37	31.32	31.20
R^2	0.93	0.93	0.93
N	2818	2818	2818

Note: All models include state fixed effects. The models in subtable *a* control for each locality's average Democratic vote share in presidential elections for this time period. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Table A.4: Statewide NO_2

	(1)	(2)	(3)
DV: $NO2_t$ (statewide)			
$NO2_{t\text{-}1}$ (statewide)	0.648***	0.624***	0.624***
	(0.026)	(0.026)	(0.026)
ΔGRP_t (statewide)	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
$\Delta Search_{t\text{-}1}$	-0.080		-0.104
	(0.081)		(0.080)
$\Delta Enforce_{t\text{-}1}$	-1.703***		-0.195
	(0.448)		(0.469)
$\Delta Search_{t\text{-}1}$ (statewide)		-0.294**	-0.286**
		(0.099)	(0.100)
$\Delta Enforce_{t\text{-}1}$ (statewide)		-8.818***	-8.743***
		(0.913)	(0.974)
F Statistic	974.29	1008.54	971.87
Resid. Std. Error	23.28	22.90	22.91
R^2	0.95	0.95	0.95
N	2907	2907	2907

Note: Estimator: OLS. State fixed effects included. $^{\dagger}p< 0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

A.4 Controlling for Statewide NO_2

Table A.5: Controlling for Statewide NO2 (5 terms)

	(1)	(2)	(3)
DV: $NO2_t$			
$NO2_{t\text{-}1}$	0.812***	0.814***	0.812***
	(0.008)	(0.008)	(0.008)
$NO2_t$ (statewide)	0.752***	0.758***	0.758***
	(0.018)	(0.019)	(0.019)
ΔGRP_t	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
$\Delta Search_{t\text{-}1}$	-0.177*		-0.182*
	(0.088)		(0.088)
$\Delta Enforce_{t\text{-}1}$	-1.305**		-1.457**
	(0.482)		(0.512)
$\Delta Search_{t\text{-}1}$ (statewide)		0.168	0.179
		(0.110)	(0.110)
$\Delta Enforce_{t\text{-}1}$ (statewide)		-0.098	0.812
		(1.007)	(1.071)
F Statistic	1056.62	1052.93	1018.83
Resid. Std. Error	24.86	24.90	24.85
R^2	0.95	0.95	0.95
N	2818	2818	2818

Note: Estimator: OLS. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

A.5 PM2.5 Models

Table A.6: Local PM2.5 (5 terms)

	(1)	(2)	(3)
DV: PM2.5$_t$			
PM2.5$_{t\text{-}1}$	0.457***	0.456***	0.453***
	(0.021)	(0.021)	(0.021)
ΔGRP$_t$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
ΔSearch$_{t\text{-}1}$	-0.010*		-0.010*
	(0.004)		(0.004)
ΔEnforce$_{t\text{-}1}$	0.024		0.011
	(0.027)		(0.029)
ΔSearch$_{t\text{-}1}$ (statewide)		0.007	0.008
		(0.005)	(0.006)
ΔEnforce$_{t\text{-}1}$ (statewide)		0.086	0.072
		(0.059)	(0.063)
F Statistic	112.25	112.18	108.32
Resid. Std. Error	1.21	1.21	1.21
R^2	0.73	0.73	0.73
N	2261	2261	2261

Note: Estimator: OLS. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

A.6 Spatial Models

In this section, I show the results for a series of SAR models with NO_2 as the DV. Equation B.1 is the specification for the SAR models. $\rho W_t(NO2_{i,t})$ represents the effect of NO_2 spillover between each city j in year t and its neighbors on the dependent variable. More specifically, ρ is the spatial parameter we fit by maximum likelihood and W_t is the adjacency matrix for all localities each year. A pair of localities is defined as adjacent if their center points are within the radii indicated in the tables below. Province fixed effects are excluded because they would be redundant in SAR models that are designed to account for neighborhood spillover effects. Estimates were obtained using 'spdep' 0.7-7 in R Open 3.5.1. Because these are SAR models, the coefficient estimates are not directly interpretable and not shown. Tables A.7 and A.8 displays the total impacts of each EV, which are comparable to coefficients in a non-spacial model.

$$\begin{aligned} NO2_{j,t} &= \alpha_{7,0} + \rho W(NO2_{j,t}) + \beta_{7,1} NO2_{j,t\text{-}1} \\ &+ \beta_{7,2} \Delta GRP_{j,t} + \beta_{7,3} Search_{j,t\text{-}2} + \beta_{7,4} \Delta Search_{j,t\text{-}1} \\ &+ \beta_{7,5} Enforcement_{j,t\text{-}2} + \beta_{7,6} \Delta Enforcement_{j,t\text{-}1} + e_{7,j,t} \end{aligned} \tag{A.1}$$

Table A.7: SAR Impacts (200km Radius)

	Dependent variable:		
	$NO2_t$		
	(1)	(2)	(3)
$NO2_{t\text{-}1}$	0.917***	0.916***	0.915***
ΔGRP_t	0.001***	0.001***	0.001***
Search $index_{t\text{-}2}$	−0.003*		−0.007***
ΔSearch $index_{t\text{-}1}$		−0.004**	−0.008***
$Enforcement_{t\text{-}2}$	−0.045**		−0.022
$\Delta Enforcement_{t\text{-}1}$		−0.413***	−0.384***
N	3,000	3,000	3,000
ρ	0.184***	0.184***	0.185***
Log Likelihood	−15,192.850	−15,184.770	−15,178.210
σ^2	1,455.575	1,447.831	1,441.365
AIC	30,399.690	30,383.550	30,374.420
Wald Test (df = 1)	341.172***	340.816***	345.250***
LR Test (df = 1)	340.831***	340.418***	345.448***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.8: SAR Impacts (400km Radius)

	Dependent variable:		
	$NO2_t$		
	(1)	(2)	(3)
$NO2_{t\text{-}1}$	0.940***	0.938***	0.939***
ΔGRP_t	0.001***	0.001***	0.001***
Search $index_{t\text{-}2}$	−0.004**		−0.008***
ΔSearch $index_{t\text{-}1}$		−0.004**	−0.009***
$Enforcement_{t\text{-}2}$	−0.032		−0.010
$\Delta Enforcement_{t\text{-}1}$		−0.375***	−0.356***
N	3,000	3,000	3,000
ρ	0.159***	0.157***	0.160***
Log Likelihood	−15,263.760	−15,257.110	−15,248.710
σ^2	1,534.767	1,528.051	1,519.391
AIC	30,541.520	30,528.210	30,515.420
Wald Test (df = 1)	207.780***	203.292***	213.593***
LR Test (df = 1)	199.001***	195.754***	204.441***
Note:			*p<0.1; **p<0.05; ***p<0.01

A.7 Air Pollution Data

The DOMINO grids for NO_2 have a resolution of 0.125 by 0.125 degrees (around 12.5 by 12.5 km at the equator). Most metro areas straddle multiple grid spaces, so I calculate municipal NO_2 concentrations as the weighted means of the grid spaces each CBSA occupies. To calculate the weighted means, I up-sample the monthly grids to 0.0125 by 0.0125 degrees using bilinear interpolation[1] and take the mean of all grid squares that are partially or entirely within each CBSA's boundary.

To increase the spatial coverage of the NO_2 data, I supplement the DOMINO data with grids from the TM4NO2A dataset. The TM4NO2A data have near-total spatial coverage, but only a quarter of the resolution of DOMINO. I therefore use DOMINO as my primary data source and use TM4NO2A to fill in its holes. I do this by up-sampling the TM4NO2A grids to 0.0125 by 0.0125 degrees and rescaling its values with a linear function so that they better correspond to the DOMINO data. The function is derived from the relationship between the values where DOMINO and TM4NO2A overlap. The grids I use are for the monthly means, not the daily overpass values. Air pollution varies substantially by season, but its time series within season is stationary (Wang and Lu 2006); one can ignore missing days but not missing months to calculate an accurate annual average.

A.8 Alternate Public Concern–Pollution Mechanisms

In general, public concern's effect on individual-level behaviors that affect air pollution levels is negligible over the course of a single decade. The individual-level behaviors that are most sensitive to concern center on reducing immediate exposure to air pollution by, for example, rescheduling travel to days with less smog. Such changes have virtually

[1]Bilinear interpolation treats the values associated with the original grid spaces as points at the exact center of each grid square and then calculates the values for the smaller 0.0125 by 0.0125 degree squares as averages of the four closest points weighted by inverse distance. I use this interpolation method because it is conservative; it does not introduce values outside the range of the original data and makes no assumptions about the presence of geographic boundaries (such as mountain ranges) or prevailing winds.

no net effect on an area's average pollution levels over the course of a year (see Welch, Gu, and Kramer 2005). Some studies have found evidence of public concern leading to durable decreases in pollution-generating activities like driving, but even these only find very small substantive effects over a single decade (e.g., Tribby et al. 2013).

Environmental activism is, of course, driven by public concern. In principle, it is possible that activists could use mechanisms that are completely independent of the political system to drive away polluters (boycotts or vandalism, for example). In practice, however, environmental activism focuses to a very large extent on pressuring various governing authorities to take action in some way (see Basu and Devaraj 2014; Lubell et al. 2006).

Public concern with air pollution can affect economic activities through non-policy mechanisms. In particular, public concern may lead people to migrate from high pollution areas (Chen, Oliva, and Zhang 2018), and industries may relocate in the face of mounting public criticism. The resulting changes in the economic activities that emit pollution are controlled for with a variable for year-on-year change in a locality's economic output.

Appendix B

Supplemental Information for Chapter 3

B.1 Summary Statistics

Table B.1: Summary Statistics

	Mean	S.D.	Min	Max
Search_t	127.3817	126.9788	1	813
$\text{Search}_{t\text{-}1}$	97.44086	109.1976	0	681
$\text{Search}_{t\text{-}2}$	59.98522	81.92618	0	635
$\Delta\text{Search}_{t\text{-}1}$	31.11416	57.76849	-102	450
Local Reports_t	0.1367572	0.09374357	0	0.7230812
Local $\text{Reports}_{t\text{-}1}$	0.132685	0.08983461	0	0.6665602
Provincial Reports_t	0.1526494	0.07978149	0	0.4132892
Provincial $\text{Reports}_{t\text{-}1}$	0.1448441	0.07764163	0	0.4132892
National Reports_t	0.05781821	0.01164571	0.04637322	0.07359706
National $\text{Reports}_{t\text{-}1}$	0.05810423	0.0119169	0.04637322	0.07359706
Reports (all levels)$_t$	0.3472248	0.1358373	0.0781004	0.9131261
Reports (all levels)$_{t\text{-}1}$	0.3356333	0.1289475	0.0781004	0.9232285
Reports (all levels)$_{t\text{-}2}$	0.1339172	0.09590861	0	0.8369084
ΔReports (all levels)$_{t\text{-}1}$	0.004634141	0.09924391	-0.4717002	0.4290939
PM2.5_t	37.74399	17.04742	4.987727	85.92473
$\text{PM2.5}_{t\text{-}1}$	36.45955	16.07568	4.672019	85.92473
$\Delta\text{PM2.5}_t$	1.28444	6.183778	-15.32011	26.42214
$\Delta\text{PM2.5}_{t\text{-}1}$	0.4273642	5.454049	-15.32011	21.72525
Upwind PM2.5_t	38.79755	16.39091	2.732214	79.66465
Neighbors' PM2.5_t	36.76062	20.7709	0	109.0396
NO2_t	627.27	476.3043	49.42042	2202.971
$\text{NO2}_{t\text{-}1}$	685.1838	523.8973	48.69183	2454.987
ΔNO2_t	-57.91383	114.5819	-860.7663	273.4408
$\Delta\text{NO2}_{t\text{-}1}$	-52.59149	123.3851	-860.7663	273.4408
Upwind NO2_t	670.43	458.5298	17.16117	2167.16
Neighbors' NO2_t	612.4214	508.981	0	2813.165
ΔGRP_t	23.47799	27.73119	1.802105	239.9957
GRP percap (ln)$_t$	10.68973	0.6094232	9.026076	13.3236
State $\text{media}_{t\text{-}1}$	16.52823	27.99225	0	233
$\Delta\text{State media}_t$	6.590054	17.76298	-141	137

This table is for 744 complete obs. The SEM's rescale some of the variables. For the NO2 SEM's, grp.adj.a.change * 10, grp.percap.adj.a.log * 1000, Reports * 1000.

B.2 Basic Linear Regression Results ($PM_{2.5}$)

B.3 Basic Linear Regression Results (NO_2)

For each EV of interest, X, these models properly distinguish between the effects of X and ΔX by using a lag structure that avoids making one a function of the other.

Note that both $\Delta Search_{t\text{-}1}$ and $Search_{t\text{-}2}$ have robust positive effects on searches and $\Delta NO2_t$ and $NO2_{t\text{-}1}$ have robust effects on air pollution. These results suggest that both variables have both short-term effects from year-on-year change, and longer term effects—the non-change EV's are themselves functions of change in previous years.

B.4 $PM_{2.5}$ SEM's

Table B.4: SEM's with $PM_{2.5}$ Pollution Measure

	(1)	(2)	(3)	(4)
DV: Search$_{t\text{-}1}$				
Search$_{t\text{-}2}$	1.066***	1.057***	1.066***	1.063***
	(0.024)	(0.024)	(0.024)	(0.024)
ΔPM2.5$_{t\text{-}1}$	0.224***	0.351***	0.224***	0.304***
	(0.031)	(0.031)	(0.031)	(0.031)
PM2.5$_{t\text{-}1}$	0.067***	0.060***	0.067***	0.063***
	(0.011)	(0.011)	(0.011)	(0.011)
Reports$_{t\text{-}1}$	-0.015	-0.013	-0.015	-0.014
	(0.014)	(0.014)	(0.014)	(0.014)
GRP percap (ln)$_{t\text{-}1}$	2.762***	2.736***	2.762***	2.734***
	(0.299)	(0.301)	(0.299)	(0.300)
DV: Reports$_t$				
Reports$_{t\text{-}1}$	0.202***	0.202***	0.202***	0.202***
	(0.038)	(0.038)	(0.038)	(0.038)
ΔPM2.5$_{t\text{-}1}$	0.207**	0.207**	0.207**	0.207**
	(0.073)	(0.073)	(0.073)	(0.073)
PM2.5$_{t\text{-}1}$	-0.010	-0.010	-0.010	-0.010

	(0.047)	(0.047)	(0.047)	(0.047)
$\text{Search}_{t\text{-}1}$	0.035	0.035	0.035	0.035
	(0.042)	(0.043)	(0.042)	(0.043)
GRP percap $(\ln)_t$	1.202	1.201	1.204	1.203
	(0.846)	(0.845)	(0.846)	(0.846)
DV: PM2.5_t				
$\text{PM2.5}_{t\text{-}1}$	0.865***	0.893***	0.572***	0.592***
	(0.023)	(0.024)	(0.022)	(0.022)
Upwind PM2.5_t			0.577***	0.568***
			(0.025)	(0.025)
ΔGRP_t	0.442***	0.326***	0.305***	0.238***
	(0.091)	(0.090)	(0.070)	(0.070)
$\text{Search}_{t\text{-}1}$	-0.090***	-0.155***	-0.030†	-0.070**
	(0.023)	(0.028)	(0.018)	(0.021)
Reports_t	-0.022	-0.018	-0.012	-0.010
	(0.019)	(0.019)	(0.015)	(0.014)
GRP percap $(\ln)_t$	-0.457	0.376	0.277	0.772*
	(0.476)	(0.484)	(0.367)	(0.374)
Feedback	No	Yes	No	Yes
Akaike (AIC)	14646	14630	14257	14244
Adj. BIC (SABIC)	14744	14729	14356	14345
R^2 (Eqn. 1)	0.83	0.82	0.83	0.82
R^2 (Eqn. 2)	0.45	0.45	0.45	0.45
R^2 (Eqn. 3)	0.90	0.90	0.94	0.94
N	744	744	744	744

Note: N = 744. All models control for the log of each observation's per capita economic output. The Reports and $\text{PM}_{2.5}$ equations include province fixed effects. Estimated using 'lavaan' v0.6-2 in R Open 3.5.1.
†p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

B.5 NO_2 SEM's

Table B.5: SEM's with NO_2 Pollution Measure

	(1)	(2)	(3)	(4)
DV: $\text{Search}_{t\text{-}1}$				
$\text{Search}_{t\text{-}2}$	1.080***	1.078***	1.080***	1.079***
	(0.024)	(0.024)	(0.024)	(0.024)
$\Delta\text{NO2}_{t\text{-}1}$	0.093***	0.113***	0.093***	0.109***
	(0.015)	(0.015)	(0.015)	(0.015)

$NO2_{t\text{-}1}$	0.031***	0.032***	0.031***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
$Reports_{t\text{-}1}$	-0.001	0.002	-0.001	0.001
	(0.014)	(0.014)	(0.014)	(0.014)
GRP percap $(\ln)_{t\text{-}1}$	0.023***	0.023***	0.023***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
DV: Reports$_t$				
$Reports_{t\text{-}1}$	0.206***	0.204***	0.205***	0.205***
	(0.038)	(0.038)	(0.038)	(0.038)
$\Delta NO2_{t\text{-}1}$	0.111***	0.112***	0.112***	0.112***
	(0.033)	(0.033)	(0.033)	(0.033)
$NO2_{t\text{-}1}$	0.031*	0.030*	0.030*	0.030*
	(0.014)	(0.014)	(0.014)	(0.014)
$Search_{t\text{-}1}$	0.038	0.038	0.038	0.038
	(0.041)	(0.041)	(0.041)	(0.041)
GRP percap $(\ln)_t$	0.005	0.006	0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)
DV: NO2$_t$				
$NO2_{t\text{-}1}$	0.862***	0.866***	0.752***	0.757***
	(0.013)	(0.012)	(0.015)	(0.015)
Upwind $NO2_t$			0.232***	0.228***
			(0.019)	(0.020)
ΔGRP_t	1.171***	1.072***	0.992***	0.926***
	(0.156)	(0.156)	(0.143)	(0.144)
$Search_{t\text{-}1}$	-0.336***	-0.399***	-0.213***	-0.261***
	(0.038)	(0.045)	(0.036)	(0.043)
$Reports_t$	-0.093**	-0.085**	-0.090**	-0.085**
	(0.033)	(0.032)	(0.030)	(0.030)
GRP percap $(\ln)_t$	0.023**	0.030***	0.027***	0.032***
	(0.008)	(0.008)	(0.008)	(0.008)
Feedback	No	Yes	No	Yes
Akaike (AIC)	25255	25246	25130	25125
Adj. BIC (SABIC)	25351	25344	25228	25225
R^2 (Eqn. 1)	0.82	0.82	0.82	0.82
R^2 (Eqn. 2)	0.46	0.46	0.46	0.46
R^2 (Eqn. 3)	0.96	0.96	0.97	0.97
N	731	731	731	731

Note: N = 731. All models control for the log of each observation's per capita economic output. The Reports and NO2 equations include province fixed effects. Estimated using 'lavaan' v0.6-2 in R Open 3.5.1. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

B.6 Note on SEM Lag Structure

Note that the SEM lag structure are different from that in the basic linear regression models. The *Search* DV is lagged by one year (and its EV's are lagged accordingly) so that it matches the lag of the *Search* EV in the NO_2 (and $PM_{2.5}$) equation. This is necessary for specifying the error correlation we predict in the model. The lag structure for the EV's is also simplified—for an EV X, X and ΔX now have the same lag—for SEM estimation tends to fail in the presence of more complicated lag structures among related variables (see Wothke 1993). We drop Δ*Search* and Δ*Reports* as EV's because they are not significant when included with their non-delta counterparts. This is because they contain largely redundant information, which greatly inflates their standard errors.[1] NO_2 and ΔNO_2 (as well $PM_{2.5}$ and $\Delta PM_{2.5}$) remain as EV's because they both have consistently significant effects, despite containing partially redundant information.

B.7 Air Pollution Measurement

We calculate each city's annual NO_2 level using the DOMINO (version 2) and TM4NO2A (version 2.3) datasets provided by the European Space Agency, which are derived from the daily overpass measurements of the OMI, MetOp-A and MetOp-B sensors. We combine these datasets to achieve near-total spatial coverage of China by a process we describe in Appendix B.13. The $PM_{2.5}$ values are from the Global Annual $PM_{2.5}$ Grids provided by NASA's Socioeconomic Data and Applications Center, which are derived using measurements from the MODIS, MISR, and SeaWiFS sensors.

City boundaries are defined as level two administrative units (known as prefectures

[1] X_t is a function of ΔX_t and X_{t-1}, and ΔX_t is a function of X_t and X_{t-1}.

Table B.2: OLS Regressions with PM2.5

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	0.963***	0.987***	0.964***
	(0.017)	(0.017)	(0.017)
ΔPM2.5$_t$		1.533***	1.633***
		(0.262)	(0.258)
PM2.5$_{t\text{-}1}$	0.524***		0.560***
	(0.099)		(0.101)
ΔReports$_t$		-0.054	-0.161
		(0.112)	(0.132)
Reports$_{t\text{-}1}$	-0.158		-0.243†
	(0.115)		(0.137)
F Statistic	1317.17	1288.64	890.42
Resid. S.E.	46.65	46.84	46.14
R^2	0.84	0.84	0.85
N	986	952	952

(b)

	(1)	(2)	(3)
DV: Reports$_t$			
Reports$_{t\text{-}1}$	0.202***	0.205***	0.200***
	(0.040)	(0.039)	(0.040)
ΔPM2.5$_{t\text{-}1}$		0.204**	0.205**
		(0.073)	(0.077)
PM2.5$_{t\text{-}2}$	-0.047		-0.010
	(0.046)		(0.048)
ΔSearch$_{t\text{-}1}$		0.001	0.001
		(0.008)	(0.008)
Search$_{t\text{-}2}$	0.005		0.005
	(0.006)		(0.006)
F Statistic	19.77	20.23	18.91
Resid. S.E.	10.32	10.27	10.28
R^2	0.45	0.45	0.45
N	744	744	744

(c)

	(1)	(2)	(3)
DV: PM2.5$_t$			
PM2.5$_{t\text{-}1}$	0.869***	0.876***	0.884***
	(0.025)	(0.025)	(0.026)
ΔGRP$_t$	0.382***	0.385***	0.471***
	(0.097)	(0.099)	(0.104)
ΔSearch$_{t\text{-}1}$		-0.014**	-0.014**
		(0.005)	(0.005)
Search$_{t\text{-}2}$	-0.008**		-0.008*
	(0.003)		(0.003)
ΔReports$_{t\text{-}1}$		-0.039*	-0.004
		(0.016)	(0.022)
Reports$_{t\text{-}2}$	0.058**		0.055*
	(0.020)		(0.028)
F Statistic	218.00	209.19	198.17
Resid. S.E.	5.56	5.49	5.46
R^2	0.90	0.90	0.90
N	715	684	684

Note: All models control for each observation's economic output per capita log. The models in subtables *b* and *c* include province fixed effects. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

Table B.3: OLS Regressions with NO2

(a)

	(1)	(2)	(3)
DV: Search$_t$			
Search$_{t\text{-}1}$	0.966***	0.996***	0.982***
	(0.017)	(0.018)	(0.017)
ΔNO2$_t$		0.052***	0.136***
		(0.014)	(0.016)
NO2$_{t\text{-}1}$	0.023***		0.037***
	(0.003)		(0.003)
ΔReports$_t$		-0.003	-0.008
		(0.011)	(0.013)
Reports$_{t\text{-}1}$	-0.021†		-0.018
	(0.011)		(0.013)
F Statistic	1352.59	1233.64	948.85
Resid. S.E.	46.07	47.60	44.80
R^2	0.85	0.84	0.86
N	977	940	940

(b)

	(1)	(2)	(3)
DV: Reports$_t$			
Reports$_{t\text{-}1}$	0.201***	0.211***	0.201***
	(0.039)	(0.039)	(0.039)
ΔNO2$_{t\text{-}1}$		0.115***	0.150***
		(0.034)	(0.037)
NO2$_{t\text{-}2}$	0.012		0.032*
	(0.013)		(0.014)
ΔSearch$_{t\text{-}1}$		0.031	-0.015
		(0.080)	(0.082)
Search$_{t\text{-}2}$	0.038		0.063
	(0.053)		(0.054)
F Statistic	19.62	20.15	19.18
Resid. S.E.	102.25	101.39	101.07
R^2	0.45	0.45	0.46
N	735	731	731

(c)

	(1)	(2)	(3)
DV: NO2$_t$			
NO2$_{t\text{-}1}$	0.883***	0.886***	0.883***
	(0.013)	(0.014)	(0.013)
ΔGRP$_t$	9.124***	7.519***	11.297***
	(1.665)	(1.658)	(1.689)
ΔSearch$_{t\text{-}1}$		-0.303***	-0.327***
		(0.078)	(0.075)
Search$_{t\text{-}2}$	-0.362***		-0.353***
	(0.052)		(0.050)
ΔReports$_{t\text{-}1}$		-0.078**	-0.042
		(0.027)	(0.036)
Reports$_{t\text{-}2}$	0.072*		0.011
	(0.035)		(0.045)
F Statistic	633.52	607.98	612.51
Resid. S.E.	94.06	91.84	88.61
R^2	0.96	0.96	0.97
N	711	680	680

Note: All models control for each observation's economic output per capita log. The models in subtables *b* and *c* include province fixed effects. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

in China), which we take from GADM's map (version 3.6). We crosschecked the GADM map with its counterpart in the GAUL maps provided by the United Nations' Food and Agricultural Organization and made several corrections (see Appendix B.17).

B.8 Pollution Spillover

While an overwhelming majority of air pollution in cities is locally produced, some is blown in from neighbors. The amount varies by pollutant. Compared to most, NO_2 breaks down quickly and does not travel very far; non-local sources account for roughly 10 percent of a city's NO_2 (Jeong et al. 2017). $PM_{2.5}$ tends to have a substantially longer lifetime and travels farther than most other pollutants. 20 to 40 percent of a city's $PM_{2.5}$ is from non-local sources (Chan and Yao 2008).

B.9 Disaggregated Reports

Table B.6: Complete Results for Models with NO_2 Pollution Measure

	(1)	(2)	(3)	(4)
DV: Search index$_{t\text{-}1}$				
Search index$_{t\text{-}2}$	1.051***	1.049***	1.051***	1.050***
	(0.024)	(0.024)	(0.024)	(0.024)
$NO_{2,t\text{-}1}$	0.031***	0.031***	0.031***	0.031***
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.090***	0.114***	0.090***	0.106***
	(0.015)	(0.015)	(0.015)	(0.015)
Reports$_{t\text{-}1}$	-0.002	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
GRP percap (ln)$_{t\text{-}1}$	0.027***	0.028***	0.027***	0.028***
	(0.004)	(0.004)	(0.004)	(0.004)
DV: Reports$_t$				
Reports$_{t\text{-}1}$	0.356***	0.358***	0.357***	0.356***
	(0.036)	(0.036)	(0.036)	(0.036)
Provincial Reports$_t$	0.200**	0.151*	0.200**	0.195**
	(0.065)	(0.066)	(0.065)	(0.065)
National Reports$_t$	0.194	0.210	0.194	0.194
	(0.266)	(0.266)	(0.266)	(0.266)

$NO_{2,t\text{-}1}$	0.147	0.101	0.144	0.137
	(0.106)	(0.106)	(0.106)	(0.106)
$\Delta NO_{2,t\text{-}1}$	0.468†	0.495†	0.470†	0.477†
	(0.273)	(0.273)	(0.273)	(0.273)
Search index$_{t\text{-}1}$	0.316	0.274	0.316	0.317
	(0.305)	(0.305)	(0.305)	(0.305)
DV: $NO_{2,t}$				
$NO_{2,t\text{-}1}$	0.862***	0.865***	0.752***	0.756***
	(0.013)	(0.013)	(0.015)	(0.015)
Upwind $NO_{2,t}$			0.231***	0.227***
			(0.020)	(0.020)
ΔGRP_t	1.183***	1.072***	1.005***	0.941***
	(0.156)	(0.156)	(0.143)	(0.144)
Search index$_{t\text{-}1}$	-0.340***	-0.418***	-0.217***	-0.268***
	(0.039)	(0.046)	(0.037)	(0.044)
$Reports_t$	-0.008*	-0.008*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
GRP percap $(\ln)_t$	0.023**	0.033***	0.027***	0.033***
	(0.008)	(0.009)	(0.008)	(0.008)
Feedback	No	Yes	No	Yes
Comparative Fit Index (CFI)	0.99	0.99	0.99	0.99
Tucker-Lewis (TLI)	0.95	0.95	0.96	0.95
Akaike (AIC)	28321	28314	28196	28192
Bayesian (BIC)	28752	28750	28633	28633
Adj. BIC (SABIC)	28454	28448	28331	28328
R^2 (Eqn. 1)	0.83	0.83	0.83	0.83
R^2 (Eqn. 2)	0.26	0.26	0.26	0.27
R^2 (Eqn. 3)	0.96	0.96	0.97	0.97

Note: N = 731. Province fixed effects included for all equations. Estimated using 'lavaan' v0.6-2 in R Open 3.5.1. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

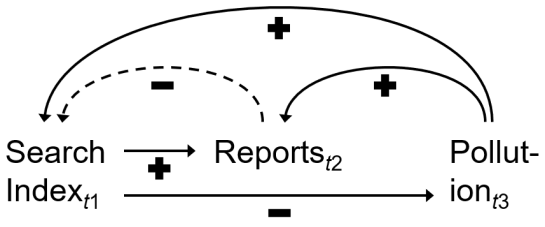
B.10 Results without Reports' Effect on Pollution

B.11 Government Work Reports Key Words

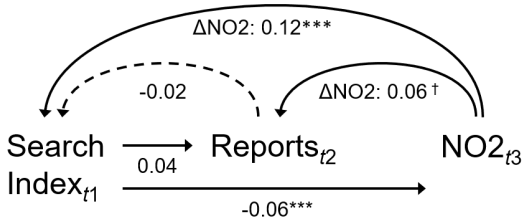
Keywords: Air Pollution (空气污染, 大气污染), Air Quality (空气质量), Atmospheric Protection (大气保护), Emissions (排放), Emissions Reduction (减排), Clean Energy (清洁能源), Environmental Pollution (环境污染), Environmental Protection (环

Figure B.1: Theoretical Expectations and Results Summary

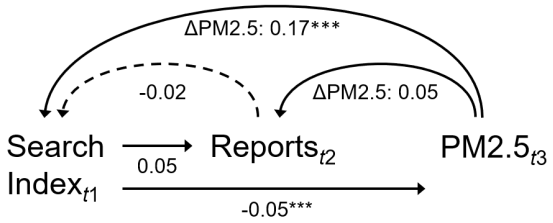
(a) Theoretical Expectations



(b) Results with NO_2 (Standardized)



(c) Results with $PM_{2.5}$ (Standardized)



Note: The arrows with plus (+) and minus (−) signs represent theorized positive and negative causal relationships respectively. The dashed arrows signify that we expect the relationship to be weak relative to air pollution's effect on the search index. $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

境保护), Green Economy (绿色经济), New Energy (新能源), Nitrogen Dioxide (二氧化氮), NO_2, NO_x, Particulate Matter (颗粒物), $PM_{2.5}$, and PM_{10}.

B.12 Newspaper Key Words

Keywords: Air Quality (空气质量), Air Pollution (空气污染, 大气污染), $PM_{2.5}$, PM_{10}, and NO_2.

B.13 Air Pollution Data Details

The DOMINO grids for NO_2 have a resolution of 0.125 by 0.125 degrees (around 12.5 by 12.5km at the equator). Most cities straddle multiple grid spaces, so we calculate municipal NO_2 concentrations as the weighted means of the grid spaces each city

occupies. To calculate the weighted means, we up-sample the monthly grids to 0.0125 by 0.0125 degrees using bilinear interpolation[2] and take the mean of all grid squares that are partially or entirely within each city's administrative boundary.

To increase the spatial coverage of our NO_2 data, we supplement the DOMINO data with grids from the TM4NO2A dataset. The TM4NO2A data have near-total spatial coverage, but only a quarter of the resolution of DOMINO. We therefore use DOMINO as our primary data source and use TM4NO2A to fill in its holes. We do this by up-sampling the TM4NO2A grids to 0.0125 by 0.0125 degrees and converting its values with a linear function so that they better correspond to the DOMINO data. The function is derived from the relationship between the values where DOMINO and TM4NO2A overlap. The grids we use are for the monthly means, not the daily overpass values. Air pollution varies substantially by season, but its time series within season is stationary (Wang and Lu 2006); we can ignore missing days but not missing months to calculate an accurate annual average.

NASA's $PM_{2.5}$ data has a resolution of 0.01 by 0.01 degrees (around 1 by 1km) and has nearly perfect spatial coverage. We therefore do not process the data before extracting the mean values for cities.

B.14 Upwind Air Pollution Control Variables

The upwind NO_2 and $PM_{2.5}$ control variables are the average annual NO_2 or $PM_{2.5}$ concentration of each city's five nearest upwind neighbors weighted by inverse distance between center points. We define upwind neighbors as level two administrative units with center points within plus or minus 90 degrees of the direction from which a city's prevailing wind blows. The averages include upwind neighbors outside of China, which are the level

[2]Bilinear interpolation treats the values associated with the original grid spaces as points at the exact center of each grid square and then calculates the values for the smaller 0.0125 by 0.0125 degree squares as averages of the four closest points weighted by inverse distance. We use this interpolation method because it is conservative; it does not introduce values outside the range of the original data and makes no assumptions about the presence of geographic boundaries (such as mountain ranges) or prevailing winds.

2 administrative units of bordering countries. Each city's prevailing wind direction was calculated as the annual circular average of daily estimates from the NOAA/NCEP Global Forecast System Atmospheric Model collection. The daily estimates are for each city's wind direction and speed at 11:00 A.M. local time.

B.15 Adding Neighborhood Air Pollution Controls

Table B.7: NO_2 SEM's with Neighborhood Pollution Controls

	(1)	(2)	(3)	(4)
DV: Search index$_{t-1}$				
Search index$_{t-2}$	1.051***	1.049***	1.051***	1.050***
	(0.024)	(0.024)	(0.024)	(0.024)
$NO_{2,t-1}$	0.031***	0.031***	0.031***	0.031***
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t-1}$	0.090***	0.114***	0.090***	0.109***
	(0.015)	(0.015)	(0.015)	(0.015)
Reports$_{t-1}$	-0.002	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
GRP percap (ln)$_{t-1}$	0.027***	0.028***	0.027***	0.028***
	(0.004)	(0.004)	(0.004)	(0.004)
DV: Reports$_t$				
Reports$_{t-1}$	0.356***	0.358***	0.358***	0.358***
	(0.036)	(0.036)	(0.036)	(0.036)
Provincial Reports$_t$	0.200**	0.151*	0.150*	0.158*
	(0.065)	(0.066)	(0.066)	(0.066)
National Reports$_t$	0.194	0.210	0.208	0.203
	(0.266)	(0.266)	(0.266)	(0.266)
$NO_{2,t-1}$	0.147	0.101	0.098	0.091
	(0.106)	(0.106)	(0.106)	(0.106)
$\Delta NO_{2,t-1}$	0.468†	0.495†	0.501†	0.507†
	(0.273)	(0.273)	(0.273)	(0.273)
Search index$_{t-1}$	0.316	0.274	0.277	0.294
	(0.305)	(0.305)	(0.306)	(0.305)
DV: $NO_{2,t}$				
$NO_{2,t-1}$	0.862***	0.865***	0.716***	0.721***
	(0.013)	(0.013)	(0.017)	(0.017)
Nbr $NO_{2,t}$			0.166***	0.165***
			(0.015)	(0.015)

ΔGRP$_t$	1.183***	1.072***	1.083***	0.993***
	(0.156)	(0.156)	(0.144)	(0.144)
Search index$_{t\text{-}1}$	-0.340***	-0.418***	-0.264***	-0.333***
	(0.039)	(0.046)	(0.036)	(0.043)
Reports$_t$	-0.008*	-0.008*	-0.007†	-0.006†
	(0.004)	(0.004)	(0.004)	(0.004)
GRP percap (ln)$_t$	0.023**	0.033***	0.030***	0.038***
	(0.008)	(0.009)	(0.008)	(0.008)
Feedback	No	Yes	No	Yes
Comp. Fit Index (CFI)	0.99	0.99	0.99	0.99
Tucker-Lewis (TLI)	0.95	0.95	0.96	0.96
Akaike (AIC)	28321	28314	28207	28198
Bayesian (BIC)	28752	28750	28643	28639
Adj. BIC (SABIC)	28454	28448	28342	28334
R^2 (Eqn. 1)	0.83	0.83	0.83	0.83
R^2 (Eqn. 2)	0.26	0.26	0.26	0.26
R^2 (Eqn. 3)	0.96	0.96	0.97	0.97

Note: N = 731. Province fixed effects included for all equations. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

B.16 SAR Models

In this section, we show the results for a series of SAR models with NO_2 as the DV.[3] Equation B.1 is the specification for the SAR models. $\rho W_t(NO2_{i,t})$ represents the effect of NO_2 spillover between each city i in year t and its neighbors on the dependent variable. More specifically, ρ is the spatial parameter we fit by maximum likelihood and W_t is the adjacency matrix for all localities each year. A pair of localities is defined as adjacent if their center points are within the radii indicated in the tables below. Province fixed effects are excluded because they would be redundant in SAR models that are designed to account for neighborhood spillover effects. Estimates were obtained using 'spdep' 0.7-7 in R Open 3.5.1. Because these are SAR models, the coefficient estimates are not directly interpretable and not shown. Table B.8 displays the total impacts of each EV, which are comparable to coefficients in a non-spacial model.

[3]Using $PM_{2.5}$ as the DV produces unstable, nonsensical results (not shown). This is because of $PM_{2.5}$'s relatively long half-life in the troposphere, which leads to higher spillover rates (over 50 percent in some cases) and greater sensitivity to complex interactions with unmeasured factors like climate and geography.

$$NO2_{i,t} = \alpha_{4,0} + \rho W_t(NO2_{i,t}) + \beta_{4,1} NO2_{i,t\text{-}1} + \beta_{4,2} \Delta GRP_{i,t} + \beta_{4,3} Search\ index_{i,t\text{-}1} + \beta_{4,4} Reports_{i,t} + \beta_{4,5} GRP\ percap_{i,t\text{-}1} + e_{4,i,t} \tag{B.1}$$

Table B.8: NO_2 SAR Model Impacts

	Dependent variable:			
	NO_2			
	(1)	(2)	(3)	(4)
$NO_{2,t\text{-}1}$	0.931***	0.937***	0.935***	0.939***
ΔGRP_t	0.700***	0.680***	0.672***	0.670***
Search $index_{t\text{-}1}$	−0.171***	−0.180***	−0.188***	−0.191***
$Reports_t$	−0.013***	−0.013***	−0.013***	−0.012***
GRP percap $(\ln)_t$	0.014*	0.017*	0.014*	0.013†
Neighborhood radius	200km	300km	400km	500km
ρ	0.154***	0.127***	0.096***	0.089***
Log Likelihood	−5,205.454	−5,224.067	−5,236.781	−5,241.747
σ^2	7,585.935	7,939.818	8,180.288	8,274.647
AIC	10,426.910	10,464.140	10,489.560	10,499.490
Wald Test (df = 1)	110.087***	73.016***	45.472***	35.270***
LR Test (df = 1)	107.315***	70.087***	44.660***	34.728***

Note: N = 884. †p< 0.1; *p<0.05; **p<0.01; ***p<0.001.

B.17 Administrative Map File Corrections

The GADM map (version 3.6) contains a redundant entry for Neijiang and incorrectly considers the polygon corresponding to Yingkou in Liaoning Province to be part of Tieling. We fix these mistakes. We checked the GADM map against the GAUL map from the United Nation's Food and Agriculture Organization. The GAUL map we used was the 2014 revision for China's level two administrative units in 2013. Level two administrative units do not change meaningfully from one year to the next.

B.18 Public Concern's Effects on Air Pollution

Over the past several decades in China, environmental activism has focused almost exclusively on pushing the government to do more about various forms of environmental degradation (Tang and Zhan 2008). Boycotts of companies do occasionally happen in China, but even in these cases, the actual target of the boycott is the government—they are a means of embarrassing or punishing local officials (Shi 1997).

Emerging scholarship shows that increasing public concern in China from 2013–2015 has influenced individual-level behaviors. However, these changes are driven by people's efforts to reduce their immediate exposure to air pollution by, for example, rescheduling travel to days with less air pollution (see Barwick et al. 2019). Such changes should have no net effect on average air pollution levels over the course of a year. Concern can influence people's polluting behaviors in the long term, but the effect typically only becomes perceptible after a decade or longer (see, for example, Tribby et al. 2013).

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