The dilemma of public information disclosures

Shi, Xiangyu and Gong, Jiaowei and Zhang, Xin and Wang, Chang

Yale

June 2024

The dilemma of public information disclosures

Jiaowei Gong[*] Xiangyu Shi[†] Chang Wang[‡] Xin Zhang[§]

July 1, 2024

Abstract

In this paper, we document a novel fact that disclosures of public information reshape social dynamics in China. Using the staggered roll-out of a quasi-natural experiment of air pollution information disclosure and a novel high-frequency data set of social and public events, we find socioeconomic cooperation and protests both significantly decrease after disclosure. The negative effects are larger when the disclosed pollution level is higher and when residents have higher environmental awareness and lower trust in local governments. Our results are rationalized in a theoretical model and suggest that information disclosure involves a trade-off between economic efficiency and political stability and leads to a dilemma for policymakers.

JEL Classification: Air pollution; Information; Social dynamics; Public events; Socioeconomic cooperation; Protests; China

Keywords: D71; D74; D9; O13; Q54; Q56

[*]Harvard University. Email: jiaowei_gong@hsph.harvard.edu

[†]Corresponding author. Department of Economics, Yale University. Email: xiangyu.shi@yale.edu

[‡]University of Michigan. Email: cwclaire@umich.edu

[§]Beijing Normal University. Email: xin.zhang614@bnu.edu.cn

1 Introduction

Information, or more specifically, public information, has social value (Feltham, 1968; Morris and Shin, 2002). In the case of air pollution, information regarding the pollution level plays a critical role in guiding individuals' decisions (Barwick et al., 2019; Wang and Zhang, 2023). The public and society also respond to the disclosed information, since it serves as a public signal for coordination (Hellwig, 2002; Morris and Shin, 2002; Angeletos et al., 2006). In this paper, we document several novel empirical facts regarding the social value of public information (disclosures). Specifically, we ask how the public disclosure of information on air pollution reshapes social dynamics—measured by social and public events—in China.[1] We use a quasi-experimental design that involves the staggered roll-out of an air pollution information disclosure policy in China and a novel high-frequency data set to provide answers. We find that public information disclosures significantly reduce both socioeconomic cooperation and protests, which have positive and negative impacts on the economy and society, respectively. Thus, information disclosure to the public has both positive and negative social values and, hence, involves a tradeoff or a dilemma. Our findings shed light on an important tradeoff for policymakers between economic efficiency and social stability. In this paper, we use air pollution information disclosure as a case in point, but our main takeaways are not subject to such a specific setting, and, can be readily applied to many other disclosures, such as epidemic diseases, that are of public interest.[2]

In theory, the incidence of public events—socioeconomic cooperation and protests in our case—is a collective action that needs coordination, which in turn relies on public information or signals. Since air pollution exerts significant impacts on a large array of socioeconomic outcomes, including productivity, cognitive capability, and physical well-being (Ghanem and Zhang, 2014; Zhang et al., 2017; Deschenes et al., 2020; among others), public information regarding air pollution serves as a critical coordinator of collective actions, including public events such as socioeconomic cooperation and protests.[3] If public information discloses an alerting level of air pollution, it will discourage economic activities including socioeconomic cooperation, since such activities may incur a higher level of disutility on participants under severe air pollution.[4] On the other hand, public information disclosure eradicates information manipulation that gives rise to political distrust and resentment of the government. Thus, it reduces incentives to engage in protests, which are a source of political instability.[5] Therefore, in

[1]In the sociology literature, social dynamics refers to the behavior of groups and the interactions of individual group members, and complicated social behaviors among humans. In this paper, we use the occurrence of public events, including socioeconomic cooperation and protests, to measure social dynamics.

[2]We provide further discussion regarding this in Section 7.

[3]We provide a formal definition of (sub-categories of) socioeconomic cooperation in Table B1.

[4]One interpretation is that receiving pollution information causes anxiety and avoidance behavior, which distracts people away from productive activities such as cooperation. The high level of air pollution itself will also cause discomfort that discourages cooperation.

[5]The alerting information of a high level of air pollution may also induce discomfort, which may be an extra reason for participating in protests since people have a relatively low return in their routine jobs and may find it more rewarding to engage in protests. Thus, receiving alerting air pollution information may discourage protests just as discouraging cooperation, but this is not consistent with our empirical findings on the role of political trust in governments, and, thus, cannot be best reconciled with all empirical evidence.

sum, in situations with a high level of air pollution and environmental awareness, pollution information disclosure has both negative and positive impacts on the economy and society and involves a dilemma: it discourages both socioeconomic cooperation and protests, leading to a lower level of economic prosperity and a high level of political stability. We also construct a theoretical model of information transmission and disclosure in Appendix A to rationalize the above reasoning.

Our empirical analysis, which is the core of this paper, relies on the institutional setting of air pollution information disclosure policy in China from 2012 to 2014. Using the quasi-experimental nature of the policy and a regression-discontinuity and difference-in-differences design, we find that the disclosure policy significantly reduces both socioeconomic cooperation and protests: the probability of cooperation decreases by about 13.8% and the probability of protests decreases by about 51.7% in the short run (about 28% and 142% of the sample median), and 4% and 5% in the long run (about 8% and 13% of the sample median).[6] We further examine the underlying mechanisms. The negative effects are more salient during more heavily polluted periods, and in regions where the public has a stronger environmental awareness and a lower level of trust in the local government.[7] Thus, the evidence points to the explanation that disclosed information serves as an alert to the public with a high level of environmental awareness and discourages them from cooperating, and eradicating information manipulation reduces incentives to express political and environmental concerns by protesting. In particular, people can verify the information disclosed by the government by comparing it with reported air pollution from other sources, such as reported by the US consulates in China. Thus, compared with the case in which the government kept air pollution information a secret, honestly disclosing the information helps regain trust (Chen et al., 2022) and, thus, discourages protests.[8] Lastly, we conduct a back-of-the-envelope calculation based on our estimated elasticities. We find that since air pollution information disclosure reshapes social dynamics by reducing both cooperation and protests, and its positive impacts on political stability slightly dominate, it leads to a 1.38% increase in economic output.[9]

Several points are worth mentioning here. First, our results are robust to the inclusion of a large vector of control variables and fixed effects and are not sensitive to different ways of clustering standard errors. Second, the regression discontinuity analysis is robust to different choices of bandwidths and the order of polynomials, and other confounding variables do not exhibit a sharp change around the cutoff timing. Third, our results are also robust to different interpretations of policy timings. We use both the timing of **planned implementation** and **actual implementation**, and the results are quantitatively

[6]The effects in the short run are much larger than those in the long run, partly because the public may have an immediate reaction to the information disclosure.

[7]When the public has a stronger environmental awareness, receiving bad information about air pollution may discourage cooperation more. On the other hand, when people distrust the government, disclosing information and reducing information manipulation will help them regain trust and, thus, discourage protests.

[8]It is also possible in theory that disclosing alerting levels of air pollution discourages people to go on the street and protests since they tend to avoid health damages, but this explanation is not fully consistent with the story of political trust.

[9]The economic effects calculated in this paper only capture the channel of the response of social dynamics, or socioeconomic cooperation and protests, to air pollution information disclosure. The disclosure may affect economic output via other channels.

similar. Fourth, since we exploit a difference-in-differences design for causal identification, we conduct a series of event study analyses and rule out the possibility that our main results are driven by unobserved pre-treatment trends.[10] Fifth, we use different measures of outcome variables of interest, including the number of social and public events, the dummy whether the event has happened, and log transformations of the number of events, and the results are still robust. Finally, we rule out the case in which regional spillover from neighbors that disclose information on air pollution drives our main results.

The primary contribution of this paper is to provide empirical support for a theoretical argument that public information has both positive and negative social value (Morris and Shin, 2002; Delmas and Lessem, 2014; Perego and Yuksel, 2022; Hu and Zhou, 2022), using the disclosure of air pollution information as a case in point. On the positive side, information disclosure prevents information manipulation by the government and, thus, leads to fewer protests and a higher level of political stability. On the negative side, disclosure of bad news may serve as an alert of unfavorable public outcomes that arouse social awareness. This is especially the case during our sample period when China discloses unacceptably high levels of pollution. The pollution information causes anxiety and avoidance behavior, which distracts people away from production activities such as cooperation. We use a novel data set that records public events in China and provides the first set of empirical facts regarding how social dynamics—measured by the incidence of socioeconomic cooperation and protests—are reshaped by information disclosure, thus empirically revealing the social value of public information. These empirical findings can also be perfectly matched with a theoretical model of information disclosure a la Crawford and Sobel (1982). Our important policy implication is that disclosing information to the public may involve a tradeoff or a dilemma: reducing political instability by terminating public information manipulation and reducing economic efficiency by delivering transparent public bad news that discourages economic activities. We also calculate the effects on economic output based on a back-of-the-envelope method.

Second, our paper also contributes to the research examining the responses to regulator-enforced environmental information disclosure. One direct outcome of pollution information disclosure is household avoidance behavior. Several studies have examined the effects of information disclosure in different settings. Using the quasi-natural experiment of smog alerts in Southern California, Neidell (2009) and Zivin and Neidell (2009) document that people spend more time indoors following the heightened environmental awareness. Shi et al. (2023) and Xie et al. (2023) also find a decrease in outdoor activities in response to pollution information in China. Households also respond to pollution information by increasing defensive expenditure, such as masks, air filters, etc. (Barwick et al., 2019; Greenstone et al., 2022; Wang and Zhang, 2023). Additionally, Chen et al. (2023) find that pollution information disclosure enhances political trust, but the positive relationship is adversely affected when the disclosed pollution level is high. Pollution information also affects other entities and markets, such as decreasing housing prices (Chay and Greenstone, 2005; Gao et al., 2021; Marcus and Mueller, 2023; Pinchbeck et al., 2023) and disciplining firms by reducing firms' regulation violation behavior (Bennear and Olmstead, 2008). Our paper expands the understanding of the various responses and outcomes associated with

[10]The results are also robust when we use the method proposed by De Chaisemartin and d'Haultfoeuille (2020) and Borusyak et al. (2021).

pollution information disclosure, providing valuable insights into how environmental information affects social dynamics, which is a novel outcome variable of interest in the literature. We also establish a novel conceptual argument that information disclosure creates a trade-off that is well connected to the theoretical literature.

Third, this paper is related to the literature on the determinants of social dynamics, and social and public events. There are several recent papers on protests in China (Cantoni et al., 2019; Bursztyn et al., 2021; Cantoni et al., 2023), and other countries (Wallace et al., 2014). More closely related, two recent papers study the effects of environmental factors on protests in China (Huang and Li, 2023; Li and Meng, 2023). However, there is little research that empirically examines the determinants of socioeconomic cooperation. Our paper fills the gap by focusing on a different outcome—socioeconomic cooperation—and its economic implications. Our paper also speaks to the literature on collective actions, using cases of cooperation and protests. Sandler and Hartley (2001) provide an excellent review of this area of research. In particular, in the famous work of Ostrom (2000), the author associates collective actions with social norms. Our paper makes further conceptual contributions that information disclosure policies can shape such social norms or public cognition regarding the government, and, thus, affect social dynamics and collective actions.

Finally, our findings also shed light on the negative effects of air pollution on various socioeconomic outcomes. Such negative effects are the premise of our conceptual framework since the detected negative effects on socioeconomic cooperation are highly related to the alerting level of air pollution and its negative impacts on various outcomes. Air pollution can raise both the mortality and morbidity rates (Chen et al., 2013; Schlenker and Walker, 2016); reduce happiness and increase the risk of mental illness (Levinson, 2012; Zhang et al., 2017); impede cognitive performance (Zhang et al., 2018); and reduce the labor supply (Hanna and Oliva, 2015) and labor productivity (Chang et al., 2016; Chang et al., 2019; Graff Zivin and Neidell, 2012). These studies form the basis of our conceptual framework, leading us to study the impacts of disclosure of air pollution information on novel outcomes: social dynamics.

The remainder of this paper proceeds as follows. Section 2 introduces the background. Section 3 lays out the conceptual framework, develops the hypotheses, and builds a theoretical model. Section 4 describes the data. Section 5 discusses the empirical strategy. Section 6 presents and analyzes the empirical results. Section 7 concludes.

2 Background

Social dynamics refers to the patterns of interaction, behavior, and relationship among individuals and groups within a society. As a canonical paper by Montroll (1978) shows, the rate of change in social evolutionary processes is considered constant, while the outbreak of public events causes deviation. Public events may serve as a catalyst for social dynamics by creating a platform for communication, expression, and mobilization. Cooperation, for example, helps mobilize groups toward a common goal, while protests, provide a platform for groups to publicly express their opinions. Public events of cooperation and social protests are also considered social movements that would foster a sense of collective identity and a shared narrative or purpose (Polletta and Jasper, 2001). Given the above reasoning, we use the incidence of public events as a measure of social dynamics.

In this paper, we relate the social dynamics in China to the staggered roll-out of a quasi-natural experiment that discloses information on air pollution. Air pollution in developing countries has been a significant environmental concern with detrimental impacts on public health and the overall well-being of its population. However, information on local pollution levels is generally not collected or disclosed[11]. In China's case, real-time data on air pollution, particularly PM2.5 concentration, was largely unavailable to the public before 2012. Although the Ministry of Environmental Protection (MEP) started publishing a daily Air Pollution Index (API) in 2000 for over 40 major cities, the API data was collected manually and the authenticity was unverified. The API data did not include data on PM2.5, which has been recognized as a major contributor to air pollution in China.

In face of the severe air pollution and limited information, the Chinese government rolled out a pollution information disclosure program in 2012, aiming to establish an automated nationwide monitoring network that collected and shared pollution information with the public. The program installed new monitoring equipment, with the recorded pollution level shared with the public in real time. The first wave of the program launched in 74 socioeconomically important cities, i.e., metropolises and provincial capitals, and are required to complete the monitoring equipment installation by January 1, 2013. The second wave involved cities on the lists of Environmental Improvement Priority Cities and National Environmental Protection Exemplary Cities, totaling 116 cities. The second wave is required to join the system by January 1, 2014. The lists of the second wave of cities were compiled by 2007, far ahead of the timing of pollution information disclosure. The remaining 177 cities were included in the third wave, which was required to implement automation by January 1, 2014. Such a feature of staggered roll-out in predetermined lists of cities allows us to implement a difference-in-differences estimation to gauge its impacts on social dynamics. By 2016, the newly established monitoring network covered over 98% of the country. Such information disclosure policy also aligns with the high public awareness of the importance of air quality, especially after the release of the documentary "Under the Dome."

Several features of the pollution information disclosure policy are worth noting. First, the newly disclosed information can be easily accessed through various channels, including governments' websites, mobile apps, etc. Today, the automated monitoring system gathers data from over 1600 monitoring stations, providing real-time updates on air pollution. An increase in news media coverage of pollution after the information disclosure is also documented by Barwick et al. (2019). Second, the timing of different batches was determined by the central government, and the classification of cities into the three batches was based on predetermined hierarchical classes. Although a few cities' designated wave deviate from hierarchical classes, these deviations are primarily due to geographic contiguity, instead of socioeconomic considerations (Barwick et al., 2019). Table B3 also suggests that the timing of the implementation is not strongly correlated with air pollutant emissions, conditional on key socioeconomic

[11] As noted by Barwick et al. (2019), out of the 20 countries with the highest levels of fine particulate matter (PM2.5) pollution, only four (Nepal, Saudi Arabia, India, and China) have installed monitoring facilities in 2018.

variables such as per capita GDP and population. The timings, however, are correlated with the pre-treatment level of some socioeconomic outcomes, consistent with the policy design that the selection and timing are partly determined by the political ranking/hierarchy of the cities. To achieve causal identification, such factors can be controlled for by including city and year-month fixed effects and time trends. We also control for these factors in the difference-in-differences design in Table B4 and the results are still robust. The spatial distribution of planned policy timing is presented in Figure B2.[12] Finally, in our sample, China experiences a period in which air pollution is severe and the public displays strong concerns about the poor air quality. Thus, this disclosure of information delivers transparent bad news to the public. This fact is relevant to the mechanism at play in which the public is discouraged from cooperating after receiving such an alerting level of air pollution.

This information disclosure policy provides an ideal context for our study of the causal impact of information disclosure on social dynamics. First of all, the disclosure of air pollution information has greatly improved the quality of pollution data and extended public access to such information. Importantly, as noted by (Barwick et al., 2019), the roll-out schedule for monitoring stations and information disclosure was unrelated to day-to-day fluctuations in local pollution levels. Second, the three-wave schedule was based on predetermined hierarchical designations, and we have shown that air pollution concentration variations were largely unrelated to different cities' roll-out dates. Additionally, there were no major national policies that coincided with the schedule or spatial coverage of the information program. Therefore, causality can be established by regression discontinuity after validating covariate balance and by difference-in-differences after obtaining satisfactory event analysis results.

3 Hypotheses Development

In this section, we first verbally develop hypotheses to be empirically tested, and, in Appendix A, build a mathematical model of information transmission between the government and the public to rationalize the hypotheses. In particular, we provide four theoretical propositions, each of which perfectly matches the hypotheses and is empirically supported.

Individuals and society as a whole respond to incentives, which are in turn largely determined by the information they possess. It is widely documented that air pollution is a significant factor that shapes a wide array of individuals' behavior (Chen et al., 2018; Chen et al., 2022; Fu et al., 2021; Shi et al., 2022; among others). Thus, information regarding the level of air pollution may be critical for individuals' actions. The individual-level responses to pollution information add up to those of the whole society and affect the incidence of public events and social dynamics. Our main contribution is to provide empirical evidence supporting this point.

In theory, disclosing information on air pollution has an ambiguous effect on public events, or

[12] Table B5 suggests that policy timings are correlated with environmental concerns and the policy is prioritized in cities with higher environmental concerns. However, the measures of these concerns are time-invariant, and, thus, can be fully absorbed into fixed effects. In our regression analysis, we control for these fixed effects that absorb these variations, alleviating endogeneity concerns.

socioeconomic cooperation and protests, a priori. For the effects on cooperation, on the one hand, disclosing information reduces uncertainty and doubts and, thus encourages cooperation that creates new economic opportunities for risk-averse individuals that constitute the majority of the population. However, on the other hand, disclosing information serves as an alert of unfavorable environmental quality that discourages cooperation, especially when the public has a high level of environmental awareness and when air pollution is severe. This is especially the case in China, as shown by the Background section. Therefore, we propose that pollution information disclosure reduces socioeconomic cooperation since it delivers transparent bad news about poor air quality to the public. For protests, the logic is clearer: pollution information uncovers the previously not-disclosed pollution information people always cared about, and thus, reduces distrust and resentment in the government. Therefore, there will be fewer protests under information disclosure. While open to alternative competing hypotheses, we summarize this reasoning in Hypothesis 1 as follows. Information has two-sided effects: On the positive side, information disclosure prevents information manipulation by the government and, thus, leads to fewer protests and a higher level of political stability; On the negative side, information disclosure may serve as an alert of unfavorable economic outcomes that arouse social awareness, especially when bad news is disclosed. This is the tradeoff that governments face when they disclose information to the public.

Hypothesis 1. *Air pollution information disclosure could possibly reduce socioeconomic cooperation and protests.*

We are also open to other alternatives that air pollution information disclosure increases socioeconomic cooperation and protests. For example, disclosure makes information about air pollution more transparent, and, thus, provides clearer guidance for economic activities and increases cooperation. On the other hand, disclosure reveals a high level of air pollution, and, thus, makes the public unsatisfied with government endeavors to deal with pollution, and, consequently, protests increase. In the empirical analysis, results support Hypothesis 1, not its competing alternatives.

Next, we discuss comparative statics, i.e., in what situations the effects of information disclosure on public events are more or less salient. For socioeconomic cooperation, since information disclosure serves as an alert to discourage economic activities, the negative effects are more salient when air pollution is at a higher level. For protests, since information disclosure reduces the public's concern about information manipulation, the effects are also more salient when air pollution is more severe. Thus, we summarize such reasoning in Hypothesis 2.

Hypothesis 2. *If Hypothesis 1 holds, then the negative effects of information disclosure on cooperation and protests are more salient with a higher pollution level.*

For both socioeconomic cooperation and protests, information disclosure has significant negative impacts. The underlying story also regards the public's environmental awareness and political attitudes. In particular, when the public is more aware of the damage of air pollution, the disclosed information may serve as a more effective alert to discourage socioeconomic cooperation. Meanwhile, the environmentally conscious public will feel more assured given a higher level of information disclosure and eradication of information manipulation. Thus, the public will have a weaker incentive to engage in protests. On the other hand, when individuals have a lower level of trust in the government, the discouraging effects of information disclosure on cooperation are stronger, due to a positive association between the return of cooperation and the level of political trust. When the level of political trust is lower, information increases governments' credibility more saliently, leading to larger negative effects of disclosure on protests. In particular, the public can verify information disclosed by the government using the pollution reports by the US consulate in China. Thus, compared to the case without any information transmission, transparent information disclosure by the government may help reduce political distrust in the government. Therefore, we summarize such reasoning in Hypothesis 3.

Hypothesis 3. *If Hypothesis 1 holds, then the negative effects of information disclosure on cooperation and protests are more salient when the public has a higher level of environmental awareness and a lower level of political trust.*

Finally, we have a hypothesis for the welfare effects of the information disclosure policy. The policy reduces both socioeconomic cooperation and protest, the former of which is positively related to economic outcomes, and the latter of which is negatively related to economic outcomes. In other words, the government faces a tradeoff with regard to whether or not to disclose information on air pollution. Therefore, the welfare effects of the disclosure are uncertain. We summarize this reasoning as Hypothesis 4.

Hypothesis 4. *Since air pollution information disclosure reduces both socioeconomic cooperation and protests, the sign of its net welfare effects is uncertain.*

In Section 6 where we present and analyze the empirical results, we show that all of these three hypotheses are consistent with the empirical findings. Specifically, results in Section 6.1 support Hypothesis 1, results in Section 6.2 support Hypothesis 2, results in Section 6.3 support Hypothesis 3, and results in Section 6.6 support Hypothesis 4.

4 Data

4.1 Social Dynamics and Public Events

The data on China's cooperation and protest events is derived from the Global Data on Events, Location, and Tone (GDELT) Project, which is increasingly used in studies of social unrest (Barrett et al., 2022). The GDELT project applies text analysis and machine learning methods to record salient characteristics (e.g., location, date, category, actor) of public events based on articles from a comprehensive set of global news resources. We restrict our sample to cooperation and protest events taking place in China for the period 2013-2017 and obtain 731,374 total events, comprising 681,886 cooperation events and 49,488 protest events.[13]

[13]We provide several case studies in Appendix D.

Specifically, each event is classified under the Conflict and Mediation Events Observations (CAMEO) Event and verb codebook, where socioeconomic cooperation and protests are the two most important categories. Socioeconomic cooperation includes economic, judicial, and information cooperation, all of which produce economic and social value and can be initiated by the public (not only the government). Socioeconomic cooperation mainly consists of economic and information cooperation (constitutes about 97%). The definition of three sub-categories are provided in Table B1. Protests include political dissent, hunger strikes, strikes or boycotts, obstructing passage or blocking, protesting violently or rioting, etc.

For cooperation events, we focus on the incidence of socioeconomic cooperation. We also use the number of each sub-group of cooperation for robustness checks, and the results are still mainly robust. In particular, the effects on economic cooperation itself, which constitutes about 97% of all socioeconomic cooperation events, are both economically and statistically significant. However, since judicial and information cooperation can also be classified as non-government-led socioeconomic activities, we use the sum of these three types of cooperation as the main outcome of interest. For protest events, in addition to the number of total protests, we calculate the city-level degree of protests as the mean of the extremeness of protest events, ranging from degree one for political dissent to degree six for protest violently or riot. The spatial distribution of public events is illustrated in Figure B1. As a placebo test to examine whether data quality biases our estimation, we also count the total data points of a certain city-time cell, and use the count as an outcome variable. It is assuring that information disclosure has a null effect on the count, and, thus, implying that changes in data quality are not the main driver of our results.

In the regression analysis, we use the dummy of whether the count of cooperation events and protests is strictly positive as the main dependent variables. Since 62.9% of observations for cooperation and 84.3% of observations for protests have zero counts, a dummy already possesses enough variations. However, it is reassuring that both using the count and the dummy produce consistent results. Finally, the summary statistics of these outcome variables can be found in Table B2.

4.2 Environmental Policy Data

To meet the public need for air pollution information, the Chinese government established an automated nationwide monitoring network was established to collect and report pollution information. There are three waves of the implementation of the monitoring network across 337 Chinese cities: Dec 31, 2012 (74 cities), Oct 31, 2013 (86 cities), and Nov 30, 2014 (177 cities). Therefore, it would be potentially important to examine the short- and long-run effect of policy implementation, in particular the public disclosure of pollution information, on social dynamics.

Compared to the original plan, the project was actually completed in four steps. We collected the timing of planned and actual implementation according to the historical data released by the China National Environmental Monitoring Center. The spatial distribution of the timing of planned and actual implementation is plotted in Figure B2 and Figure B3, respectively. Using the timing of the plan and implementation, we employ a regression discontinuity design and a difference-in-differences design to gauge the causal effects of the air pollution information disclosure policy. These strategies involve using a treatment dummy variable equal to one if a city has announced or implemented the policy. The summary statistics of the treatment variable can be found in Table B2.

In the empirical analysis, we use the timing of **planned implementation** as the baseline and the timing of **actual implementation** as a robustness check. The results are quantitatively similar.

4.3 Environmental Awareness and Political Attitudes

We use four waves of the Chinese Family Panel Survey (CFPS) conducted in 2012, 2014, 2016, and 2018, to obtain the province average[14] of political attitudes and environmental awareness. The CFPS provides information on the province of residence for each respondent, enabling us to match them with the location of public events and information disclosure. Especially, we focus on several main variables. First, we focus on the trust in the local government. Each survey respondent needs to provide a score of political trust, with 0 being the lowest and 10 being the highest. Second, to measure environmental awareness, we use the question of environmental concerns. Each survey respondent reports a score to express their worries about environmental issues, with 0 being no concerns about environmental issues at all and 10 being the strongest concerns. In our heterogeneity analysis to explore potential mechanisms or pathways, we calculate the time-invariant province-level average of these variables, using four waves of surveys from 2012 to 2018.

Finally, we provide summary statistics of key variables in Table B2. We also provide information on other data used in this paper in Appendix C.

5 Empirical Strategy

In this section, we discuss the empirical strategy. We use a regression discontinuity design to estimate the short-term effects, and use a difference-in-differences design to estimate the medium- and long-term effects. In particular, for either strategy, we discuss the threats to identification and how we solve them.

5.1 Short-term Effects of Environmental Policy on Social Dynamics

We first examine the short-term effect of implementing the roll-out of the air pollution information disclosure (Greenstone et al., 2022), on social dynamics: cooperation and protests. We use a regression discontinuity design to meet this end since we aim to detect a sharp change in social dynamics after the starting date of information disclosure. Such a sharp change also corresponds to the short-term effect. The main specification of the descriptive empirical analysis in this section takes the form of equation (1),

[14] We use the data of province average because all provinces are covered by the CFPS data, but only about 40% cities are covered.

using a city-year-month (or city-week/day) panel dataset and employing a linear generalized regression discontinuity (RD) design regression:

$$Y_{itm} = \beta_1 1\left(t \geq \text{Policy}_{itm}\right) + \beta_2 f\left(t - \text{Policy}_{itm}\right) + \beta_3 1\left(t \geq \text{Policy}_{itm}\right) * f\left(t - \text{Policy}_{itm}\right) + \lambda_i + \lambda_{tm} + u_{itm}, \tag{1}$$

where Y_{itm} is the outcome variable, including the dummy of cooperation and protests,[15] in the city i, year t, and month m, $1\left(t \geq \text{Policy}_{itm}\right)$ is an indicator that equals one if city i at year t and month m has implemented the roll-out. We use the timing of **planned implementation** as the baseline. $f\left(t - \text{Policy}_{itm}\right)$ is a fourth-order polynomial that allows the trend to differ before and after the automation. λ_i is city fixed effects; λ_{tm} is year-month fixed effects. In particular, the policy timing is partly determined by the political hierarchy of the cities. However, such variations can be fully absorbed into city fixed effects λ_i. u_{itm} is the error term. In main regressions, we cluster the standard errors at the city level and use optimal bandwidth as in Calonico et al. (2019). For robustness checks, we try different bandwidths and polynomials' orders.

Threats to Causal Identification The identifying assumption of the regression discontinuity design is that there is no observed discontinuity for confounding factors that may affect the timing and implementation of the roll-out. We design a series of balancing tests of these confounding factors, such as climate and socioeconomic conditions, and report the results in Table B6. There is no discernible discontinuity in these variables.

5.2 Medium- and Long-term Effects of Environmental Policy on Social Dynamics

Next, we examine the medium- and long-term effects of implementing air pollution information disclosure on social dynamics. We use a longer time horizon and a difference-in-differences design to meet this end. The estimated effects correspond to medium- and long-term ones due to the longer sample period and the nature of the difference-in-differences design that captures average treatment effects on treated instead of local average treatment effects as regression discontinuity design. The main specification of the descriptive empirical analysis in this section takes the form of equation (2), using a city-year-month (or city-week/day) panel dataset and employing a difference-in-differences (DD) regression:

$$Y_{itm} = \beta Policy_{itm} + \lambda_i + \lambda_{tm} + u_{itm}, \tag{2}$$

where Y_{itm} is the outcome variable, including the dummy of cooperation and protests, in the city i, year t, and month m, $Policy_{itm}$ refers to the planned implementation of the information disclosure at the city level. λ_i is city fixed effects;[16] λ_{tm} is year-month fixed effects. For the main part of the analysis,

[15]We also use other forms of dependent variable for robustness checks.

[16]Again, the policy timing is partly determined by the political hierarchy of the cities. However, such

we focus on 1(Cooperation (socioeconomic)) and 1(Protests) and use them as the dependent variable, but to show robustness we also use other relevant outcomes in the analysis. We cluster standard errors at the city level, to allow for city-level cross-sectional correlations of error terms. We also try different ways of clustering standard errors for robustness checks.

Threats to Causal Identification As per the Background section, the selection and timing of the roll-out are mainly determined by time-invariant factors. Therefore, the only threat to identification is the non-parallel trends between the treated and untreated cities. This issue can be fully addressed by a set of event study analyses. Therefore, to rule out the case in which our main results of difference-in-differences are driven by unobserved pre-treatment trends, we conduct an event study analysis design. The specification is

$$Y_{itm} = \sum_{\tau \neq -1} \beta_\tau Policy_i \times 1(tm = \tau) + \lambda_i + \lambda_{tm} + u_{itm}, \tag{3}$$

where $Policy_{itm}$ is replaced with a set of interaction terms, $Policy_i \times 1(tm = \tau)$. We set $\tau = -1$ as the base period and normalize the regression coefficient to zero. For robustness checks, we conduct event study designs using the method proposed in De Chaisemartin and d'Haultfoeuille (2020) and Borusyak et al. (2021).

The main potential threat to identification is the endogenous selection of roll-out cities. However, according to Section 2, the main variations contributing to roll-out timings can be absorbed into city fixed effects and key socioeconomic factors. Therefore, conditional on these variations, a set of event study analyses that show no significant pre-treatment trends between the treatment group and the control group can mitigate concerns about identification and endogeneity issues.

6 Empirical Results

6.1 Baseline Results: Testing Hypothesis 1

We start with the specification of equation (1) to estimate the short-term effects of air pollution information disclosure on social dynamics: the incidence of public events including socioeconomic cooperation and protests. For the main part of the analysis, we focus on 1(Cooperation (socioeconomic)) and 1(Protests) and use them as the dependent variable, but to show robustness we also use other relevant outcomes, including other types of cooperation, in the analysis. In the regression, we control for the fourth-order polynomial and its interaction terms with the treatment dummy. The bandwidth is 14 months before and 12 months after the cutoff, which is optimally chosen according to Calonico et al. (2019).[17] Table 1 presents the results. Column (1) indicates that the information disclosure policy reduces the probability of socioeconomic cooperation by 0.138, which is about 28% of the sample median. Columns (2) and (3) indicate that other types of cooperation also decrease after the information disclo-

variations can be fully absorbed into city fixed effects λ_i.

[17]For robustness checks, we also use alternative bandwidths, and the results are still robust.

sure. Although we focus on 1(Cooperation (socioeconomic)) in our main analysis, we show here and can show further (results available upon request) that our results are robust for other types of cooperation. Column (4) indicates that the disclosure policy reduces the probability of protests by 0.517, which is about 1.4 times the sample median. This indicates that the response of socioeconomic cooperation and protests is large in the short run. When the time window becomes longer, the estimated effects are smaller, and, thus, correspond to the long-term consequences: adaptation of the cognition and behavior of the public. To further support the regression discontinuity design, we plot the time trends of outcomes of interest before and after the treatment in Figure 1. For both local linear regressions and regressions that include fourth-order polynomials, we can see a sharp decline in the probability of cooperation and protests after the policy. In particular, the number of bins and the bandwidth are optimally chosen according to Calonico et al. (2019). Moreover, we conduct a balancing test in Table B6. We do not find a significant sharp change in other confounding variables. Finally, we also conduct the regression discontinuity design using alternative bandwidths and orders of polynomials. According to the results in Table B7, the results are still robust. However, as we use a longer time window, the magnitude of the effects is smaller, since it no longer corresponds to the sharp response in the short run.

Before interpreting the implications of the results, we first present the results of difference-in-differences estimation, as in equation (2). We report the results in Table 2. In columns (1) and (2), where we use a linear probability model with the indicator of the incidence of socioeconomic cooperation and protests being the dependent variable, the coefficients on the treatment dummy are both negative and statistically significant. However, the effects are much smaller in the medium/long run than those in the short run. For example, in column (1), the coefficient suggests that the disclosure policy reduces the probability of socioeconomic cooperation by 4.13%, which is about 8% of the sample median. We also find, in column (3), that the scale or seriousness of protests also decreases after information disclosure. Finally, in column (4), we use the ratio of the count of cooperation over the count of protests[18], the effect of the disclosure policy is also negative. This suggests that the policy reduces cooperation more than protests.

We provide our explanation as follows. According to the conceptual framework in Section 3, information disclosure may have mixed effects on social dynamics. On the one hand, it pacifies the resentment of the public by eradicating information manipulation and, thus, reduces protests. This reasoning echoes the mechanism in Greenstone et al. (2022). On the other hand, it reveals bad air quality and convinces the public that air pollution is unfavorable for economic and social activities such as socioeconomic cooperation. Such bad news discourages cooperation because it causes physical and psychological discomfort that raises the cost of cooperation. This mechanism of providing new information echoes the one in Barwick et al. (2019). Thus, Tables 1 and 2 point to the policy implication that public information disclosure may have both positive and negative welfare effects on the public. Thus, the government faces a tradeoff and a dilemma.

To validate the identification assumption of our difference-in-differences design, we conduct a series of event studies using equation (3). Figure 2 shows the results. The coefficients associated with $tm < 0$

[18]To be more specific, we use $\frac{1+Cooperation}{1+Protest}$ to avoid the issue that the denominator may be zero.

are basically non-negative and statistically insignificant, and the coefficients associated with $tm \geq 0$ are mostly negative and statistically significant at least at the 10% level.[19] Such results indicate that our main results of difference-in-differences are not driven by unobserved pre-treatment trends. We also use the timing of actual implementation and the method proposed in De Chaisemartin and d'Haultfoeuille (2020) and Borusyak et al. (2021) as robustness checks, and the results in Figures B4 and B5 are quantitatively similar.

6.2 The Role of Pollution Level: Testing Hypothesis 2

In this section, we test Hypothesis 2, which states that the negative effects of air pollution information disclosure are more salient when the level of air pollution is higher. This is the case for protests since the consequence of the eradication of information manipulation is more prominent when air pollution is more severe. This is also the case for socioeconomic cooperation since information disclosure releases alerting and negative information regarding air pollution that discourages economic activities.

To test this hypothesis, we interact the policy treatment dummy variables with the level of air pollution: PM2.5 and PM10. Therefore, the coefficient of the interaction term is the parameter of interest, and we expect it to be negative so as to be consistent with Hypothesis 2. We report the results in Table 3, and it is indeed this case. In columns (1) through (6), the coefficients on the interaction terms are all negative and statistically significant. Thus, the effects of air pollution information disclosure on socioeconomic cooperation and protests are more salient if air pollution is more severe. For robustness checks to deal with potential endogeneity of pollution levels, we use thermal inversions as an instrument for the level of air pollution and conduct a two-stage least-square estimation. The results reported in Table B8 are still robust. We also plot the event study graphs, as in a standard triple-difference setting, by interacting air pollution with the policy of information disclosure. The results are reported in Figure B6.

Thus, if public information discloses an alerting level of air pollution, it will discourage economic activities including socioeconomic cooperation, since such activities may incur a higher level of disutility on participants under severe air pollution. On the other hand, public information disclosure eradicates information manipulation that gives rise to political distrust and resentment of the government. Therefore, information reduces incentives to engage in protests, which is a source of political instability. The alerting information of a high level of air pollution may also induce discomfort, which may be an extra reason for participating in protests since people have a relatively low return in their routine jobs and may find it more rewarding to engage in protests. Thus, receiving alerting air pollution information may discourage protests just as discouraging cooperation, but this is not consistent with our empirical findings on the role of political trust in governments. Thus, in our empirical analysis, the negative effects on protests cannot be best reconciled with this mechanism. In sum, all the above results support Hypothesis 2.

[19] However, not all coefficients are statistically significant at the 5% level.

6.3 The Role of Environmental Awareness and Political Attitudes: Testing Hypothesis 3

In this section, we investigate the role of environmental awareness and political attitudes and test Hypothesis 3. According to Section 3, the negative effects of air pollution information disclosure on socioeconomic cooperation and protests should be more prominent if the public is more aware of the poor environmental conditions and has a lower level of trust in the government.

We test this argument, or Hypothesis 3, also using interaction term regressions. We interact the policy treatment dummy with an array of indicators of environmental concerns and political attitudes, which are in turn obtained using the CFPS database of 2012-2018. Each variable is constructed by calculating the provincial average of these sample years.[20] We report the results in Table 4. Note that the environmental concerns and trust are measured at the provincial level, and, thus, their coefficients are absorbed into the city fixed effects.[21] The results indeed indicate that the negative effects of air pollution information disclosure on socioeconomic cooperation and protests are more salient if the public has a stronger concern for environmental issues and has a lower level of political trust. For example, columns (1) and (4) present a negative and statistically significant interaction term, suggesting that if the citizens in a city have a higher level of concerns about environmental quality, the negative effects of the policy treatment are larger and more negative. Although the coefficient on the policy dummy is positive, the main effects evaluated on the mean value of environmental concerns are negative and statistically significant.[22] Columns (2) and (5) indicate that if the citizens in a city have a higher level of trust in the local government, then the negative effects of air pollution information disclosure are weaker. The interpretation is that when the public has a stronger environmental awareness, receiving bad information about air pollution may discourage cooperation more. On the other hand, when people distrust the government, disclosing information and reducing information manipulation will help them regain trust and, thus, discourage protests.[23] The results may also be interpreted as the baseline likelihood of protests being rather low prior to the policy in cities with strong trust in the local government, thus the information disclosure could not further decrease the protest likelihood in these cities as much as in other ones. However, when we use generalized trust to construct the interaction term in columns (3) and (6), the coefficients are not statistically significant, indicating that only environmentally and politically relevant factors are at play. It also suggests that the survey response biases are not driving our results. In sum, the results in Table 4 support Hypothesis 3.

[20] Chen et al. (2023) find that air pollution information disclosure has significant effects on trust in local government. We focus on the same policy and the same data that measures trust. However, we focus on the outcome of social dynamics or public events in this paper, which is the major difference and our contribution.

[21] There is the same issue in Tables 5 and 6.

[22] The mean value of environmental concerns is about 6.2, leading to the coefficient of the main effect of -0.0502 in column (1) and -0.0530 in column (4).

[23] Our empirical results do not support the explanation that people who distrust the government will also doubt the validity of the disclosed information and participate in protests more.

6.4 More Heterogeneity Analysis

In this section, we explore the heterogeneity of our estimated main effects. We first focus on the role of education, since education is also directly related to environmental and political awareness. An individual with a higher level of education has also a higher level of awareness of environmental and political issues. Thus, according to Hypothesis 3, the negative effects of air pollution information disclosure should be stronger when the city's citizens have a higher educational attainment. To test this argument, we calculate the share of city population above the junior high school, high school, and college level, using 2005 Population Census data,[24] and construct interaction terms with the policy treatment dummy variable. We report the results in Table 5. The interaction terms are negative and statistically significant, suggesting that the negative impacts of the disclosure policy are stronger when the citizens are more educated.[25] These results also echo Hypothesis 3.

Next, we examine the role of other socioeconomic conditions, such as GDP, population, and productivity.[26] These variables determine the return and opportunity costs of cooperation and protests. Again, we construct interaction terms between the policy treatment dummy and the socioeconomic variables. We report the results in Table 6. Column (1) suggests that the negative effects of information disclosure are stronger when the per capita GDP is higher. This may be due to the fact that people with a higher income level care more about the negative consequences of air pollution on health so the disclosed information on severe air pollution serves as a stronger alert to discourage cooperation. This is also the case for columns (3) and (4), in which the interaction terms are constructed using the mean level of productivity at the city level, using the Annual Survey of Industrial Firms database.[27] In column (2), the interaction term between the policy dummy and the population is positive and statistically significant, indicating that the negative effects of pollution information disclosure are weaker when there is a larger market size that is associated with a higher return of cooperation. This is also the case for protests, as the coefficient of the interaction term in column (6) is positive and statistically significant. The story of a higher return of protests (with a larger city population) similarly holds. For columns (7) and (8), the story is also similar, since a lower level of productivity indicates a smaller opportunity cost and a higher level of relative return of protests.

6.5 Robustness Checks

In this section, we conduct a series of robustness checks. First, we use the actual implementation dates of the air pollution information disclosure and redo the regression discontinuity and difference-in-differences estimation as in Tables 1 and 2. We report the results using the dates of actual implementation

[24]The Census data provides information on educational attainment at the individual level. We use such information to calculate the city-level share of college, high school, and junior high school graduates.

[25]Same as Table 3, although the coefficient on the policy dummy is positive, the main effects evaluated on the mean value of environmental concerns are negative and statistically significant.

[26]The data on GDP and population is obtained from Chinese City Statistics Yearbooks. The data on productivity is obtained from the Annual Survey of Industrial Firms.

[27]The data is available for the period of 1998-2007. We use ACF correction to calculate the productivity at the firm level and calculate the mean level of productivity at the city level.

in Table B9. The results are still robust.

Second, we use the counts (Y) of the public events, and also transform the count of public events into the log forms, using $log(1 + Y)$ and $arcsinh(Y)$ as the dependent variables. We report the results in Tables B10 and B11. The results are still quantitatively similar: The policy reduces socioeconomic cooperation by 37.4% in the short run and by 25.1% in the medium and long run. The magnitude of the effects is relatively larger than that of our baseline results.

Third, we add additional control variables and fixed effects in the difference-in-differences estimation. Specifically, we add economic controls, climate controls, air quality controls, and city-month fixed effects in the regressions. Economic controls include log per capita GDP, log population, and log number of firms. Climate controls include mean temperature, wind speed, humidity, and sunshine duration. Air quality controls include the levels of PM2.5, PM10, ozone, and NO_2. We present the results in Table B4, which are still quantitatively similar to the baseline results.

Fourth, we explore various alternative ways of clustering standard errors. We use robust standard errors and two-way cluster the standard errors at city and year, city and month, and city and year-month levels. We report the results in Table B12. The regression coefficients are still statistically significant with different standard errors.

Fifth, we rule out that our main results are driven by regional spillovers that are unaccounted for. Due to labor mobility, regional spillovers may be a crucial mechanism at play. To meet this end, we control for the average level of treatment of the rest of the cities in the same province. We report the results in Table B13. Adding the term representing regional spillovers does not change the main results—the coefficients of the main effects of the policy—much. We still get negative effects of air pollution information disclosure on socioeconomic cooperation and protests, which are also statistically and economically significant.

Sixth, we deal with the fuzziness of the dates of socioeconomic cooperation and protests. It is possible that the dates of public events are not fully exact. For example, cooperation and protests may last for several days and, each day could possibly enter the data set as an observation. To deal with this issue, we drop the first one to three days of each month and rerun the baseline specification. We report the results in Table B14. The results are still robust.

Seventh, we use data sets with a higher frequency. In particular, we use a city-day data set and a city-week data set to rerun our main regression discontinuity and difference-in-differences specifications. The results reported in Tables B15 and B16 are still robust. We find similar negative and statistically significant effects of the information disclosure policy on cooperation and protests, and the magnitudes are also comparable.

Eighth, we address the potential concerns with data quality. It is possible that the detected effects are mainly driven by policy-induced changes in data quality. However, given that the coverage and intensity of reporting public events in China is increasing over time, it is unlikely that the negative effects of disclosure on public events are driven by this increasing trend. Moreover, we test whether the data coverage is different before and after the policy treatment. We use the number of data points in each city as the dependent variable and rerun the regression discontinuity and the difference-in-differences estimation. We report the results in Table B17. We find null effects on the number of data points, which is a measure of data quality.

Finally, we investigate the regional and temporal heterogeneity. We divide the entire sample into six macro-regions: Northeast, North China, South China, East China, Southwest, and Northwest, and rerun the difference-in-differences estimation with each subsample. The effects are more salient for Northeast and Northwest, according to the results in Table B18. We next divide the entire sample into four seasons: spring, summer, fall, and winter, and rerun the difference-in-differences estimation with each subsample. The results in Table B19 indicate that the effects are stronger for spring and winter when air pollution is relatively more severe.

6.6 Economic Implications: Testing Hypothesis 4

In this section, we explore the economic implications of air pollution information disclosure. We do so by estimating the effects of social dynamics—socioeconomic cooperation and protests—on economic output. To deal with potential endogeneity, we exploit the treatment status of air pollution information disclosure as the instrumental variable, and conduct a two-stage-least-square (2SLS) estimation. Therefore, the effects may have a, albeit weak, causal interpretation. The identification assumption is that conditional on fixed effects and control variables, the staggered roll-out of disclosure provides plausibly exogenous identifying variations. This is plausible since such variations are mainly determined by cities' political hierarchies that are fully absorbed into fixed effects. It is also reassuring that OLS estimation produces both qualitatively and quantitatively similar results, albeit the results are relatively more subject to identification issues. Using city-year panel data from 2013 to 2017, we find in Table 7 that increasing socioeconomic cooperation by 1% raises per capita GDP by 0.0434%; increasing economic cooperation by 1% raises per capita GDP by 0.0436%; increasing protests by 1% reduces per capita GDP by 0.0366%.[28] The effects are all statistically significant at a 1 percent level.[29]

Therefore, combining the estimates in Tables 2 and 7, we can conduct a back-of-the-envelope calculation. Since air pollution information disclosure reduces the ratio of cooperation over protests by 3.195, and reduces socioeconomic cooperation by 11%, with the city-year level mean of cooperation and protests being 130.62 and 33.09, information disclosure leads to an increase in per capita GDP by 1.38%.[30] The disclosure raises the level of economic output since its GDP improvement effects through protests are larger than the GDP reduction effects through cooperation. Such results of the back-of-the-envelope calculation also reveal the tradeoff or dilemma that pollution information disclosure may involve: it reduces economic efficiency but increases political stability.

One caveat in interpreting the results is that we only consider the impacts of air pollution information disclosure on economic outputs through the mechanism of reshaping social dynamics, including

[28]The data of GDP is obtained from Chinese City Statistics Yearbooks of each related year.

[29]The results are still robust if we simply employ an OLS estimation. However, such an estimation strategy is subject to endogeneity issues.

[30]We first use the data and statistics to calculate the relative effects of information disclosure on socioeconomic cooperation (socioeconomic) and protests. Then, using the elasticity of per capita GDP with respect to cooperation and protests, we calculate the net effects on per capita GDP.

cooperation and protests. It is completely possible that there are many other potential mechanisms that are unaccounted for. Our back-of-the-envelope calculation only captures the role of the response of social dynamics.

7 Conclusion

Social dynamics are key to economic development and the evolution of society. We find public information disclosures affect social dynamics, and, thus, have social value. In this paper, we are among the first in the literature to document the fact that the disclosure of air pollution information reshapes social dynamics in China. Using the staggered roll-out of a quasi-natural experiment of pollution information disclosure, a regression-discontinuity design, and a difference-in-differences design, we find socioeconomic cooperation and protests significantly decrease after disclosure, both in the short and in the medium/long run.

We propose the explanation that disclosing information serves as an alert of unfavorable environmental quality that discourages cooperation, especially when the public has a high level of environmental awareness and when air pollution is severe, and that pollution information disclosure reduces misinformation and information manipulation by the government and, thus, reduces distrust and resentment in the government. Such an explanation is further supported by the fact that the negative effects are more salient during more heavily polluted periods, and in regions where the public has a stronger environmental awareness and a lower level of trust in the local government. Our results can be rationalized by a theoretical model and indicate that air pollution information may have both positive and negative social values and involve a tradeoff or a dilemma: it reduces economic efficiency but increases political stability.

Our key insights are not limited to the setting of air pollution information disclosures. On the one hand, they can be readily applied to other pollutants; on the other hand, they can be applied to many other kinds of information that is of public interest, such as epidemic diseases and construction of hazardous projects. Finally, our analysis is based on China, the second-largest economy and populous country, and, yet, it is not geographically restricted to China but is relevant to many other situations.

References

[1] G.-M. Angeletos, C. Hellwig, and A. Pavan. Signaling in a global game: Coordination and policy traps. *Journal of Political economy*, 114(3):452–484, 2006.

[2] P. Barrett, M. Appendino, K. Nguyen, and J. de Leon Miranda. Measuring social unrest using media reports. *Journal of Development Economics*, 158:102924, 2022.

[3] P. J. Barwick, S. Li, L. Lin, and E. Zou. From fog to smog: The value of pollution information. Technical report, National Bureau of Economic Research, 2019.

[4] L. S. Bennear and S. M. Olmstead. The impacts of the "right to know": Information disclosure and the violation of drinking water standards. *Journal of Environmental Economics and Management*, 56(2): 117–130, 2008.

[5] K. Borusyak, X. Jaravel, and J. Spiess. Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*, 2021.

[6] L. Bursztyn, D. Cantoni, D. Y. Yang, N. Yuchtman, and Y. J. Zhang. Persistent political engagement: Social interactions and the dynamics of protest movements. *American Economic Review: Insights*, 3(2): 233–250, 2021.

[7] S. Calonico, M. D. Cattaneo, M. H. Farrell, and R. Titiunik. Regression discontinuity designs using covariates. *Review of Economics and Statistics*, 101(3):442–451, 2019.

[8] D. Cantoni, D. Y. Yang, N. Yuchtman, and Y. J. Zhang. Protests as strategic games: experimental evidence from hong kong's antiauthoritarian movement. *The Quarterly Journal of Economics*, 134(2): 1021–1077, 2019.

[9] D. Cantoni, A. Kao, D. Y. Yang, and N. Yuchtman. Protests. Technical report, National Bureau of Economic Research, 2023.

[10] T. Chang, J. Graff Zivin, T. Gross, and M. Neidell. Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3):141–69, 2016.

[11] T. Y. Chang, J. Graff Zivin, T. Gross, and M. Neidell. The effect of pollution on worker productivity: evidence from call center workers in china. *American Economic Journal: Applied Economics*, 11(1): 151–72, 2019.

[12] K. Y. Chay and M. Greenstone. Does air quality matter? evidence from the housing market. *Journal of political Economy*, 113(2):376–424, 2005.

[13] S. Chen, P. Oliva, and P. Zhang. Air pollution and mental health: evidence from china. Technical report, National Bureau of Economic Research, 2018.

[14] S. Chen, P. Oliva, and P. Zhang. The effect of air pollution on migration: evidence from china. *Journal of Development Economics*, 156:102833, 2022.

[15] X. Chen, X. Shen, and A. Zhuge. Pollution matters: The political cost of information disclosure. *Governance*, 2023.

[16] Y. Chen, A. Ebenstein, M. Greenstone, and H. Li. Evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy. *Proceedings of the National Academy of Sciences*, 110(32):12936–12941, 2013.

[17] V. P. Crawford and J. Sobel. Strategic information transmission. *Econometrica: Journal of the Econometric Society*, pages 1431–1451, 1982.

[18] C. De Chaisemartin and X. d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American economic review*, 110(9):2964–2996, 2020.

[19] M. A. Delmas and N. Lessem. Saving power to conserve your reputation? the effectiveness of private versus public information. *Journal of Environmental Economics and Management*, 67(3):353–370, 2014.

[20] O. Deschenes, H. Wang, S. Wang, and P. Zhang. The effect of air pollution on body weight and obesity: evidence from china. *Journal of Development Economics*, 145:102461, 2020.

[21] G. A. Feltham. The value of information. *The accounting review*, 43(4):684–696, 1968.

[22] S. Fu, V. B. Viard, and P. Zhang. Air pollution and manufacturing firm productivity: Nationwide estimates for china. *The Economic Journal*, 131(640):3241–3273, 2021.

[23] X. Gao, R. Song, and C. Timmins. The role of information in the rosen-roback framework. Technical report, National Bureau of Economic Research, 2021.

[24] D. Ghanem and J. Zhang. 'effortless perfection:'do chinese cities manipulate air pollution data? *Journal of Environmental Economics and Management*, 68(2):203–225, 2014.

[25] J. Graff Zivin and M. Neidell. The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73, 2012.

[26] M. Greenstone, G. He, R. Jia, and T. Liu. Can technology solve the principal-agent problem? evidence from china's war on air pollution. *American Economic Review: Insights*, 4(1):54–70, 2022.

[27] R. Hanna and P. Oliva. The effect of pollution on labor supply: Evidence from a natural experiment in mexico city. *Journal of Public Economics*, 122:68–79, 2015.

[28] C. Hellwig. Public information, private information, and the multiplicity of equilibria in coordination games. *Journal of Economic Theory*, 107(2):191–222, 2002.

[29] J. Hu and Z. Zhou. Disclosure in epidemics. *Journal of Economic Theory*, 202:105469, 2022.

[30] Y. Huang and Y. Li. Labor activism over searing heat. *Journal of Environmental Economics and Management*, 122:102888, 2023.

[31] A. Levinson. Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics*, 96(9-10):869–880, 2012.

[32] J. Li and G. Meng. Pollution exposure and social conflicts: Evidence from china's daily data. *Journal of Environmental Economics and Management*, 121:102870, 2023.

[33] M. M. Marcus and R. Mueller. Discovery of unregulated contaminants in drinking water: Evidence from pfas and housing prices. Technical report, National Bureau of Economic Research, 2023.

[34] E. W. Montroll. Social dynamics and the quantifying of social forces. *Proceedings of the National Academy of Sciences*, 75(10):4633–4637, 1978.

[35] S. Morris and H. S. Shin. Social value of public information. *american economic review*, 92(5):1521–1534, 2002.

[36] M. Neidell. Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. *Journal of Human resources*, 44(2):450–478, 2009.

[37] E. Ostrom. Collective action and the evolution of social norms. *Journal of economic perspectives*, 14(3): 137–158, 2000.

[38] J. Perego and S. Yuksel. Media competition and social disagreement. *Econometrica*, 90(1):223–265, 2022.

[39] E. W. Pinchbeck, S. Roth, N. Szumilo, and E. Vanino. The price of indoor air pollution: evidence from risk maps and the housing market. *Journal of the Association of Environmental and Resource Economists*, 10(6):1439–1473, 2023.

[40] F. Polletta and J. M. Jasper. Collective identity and social movements. *Annual review of Sociology*, 27 (1):283–305, 2001.

[41] T. Sandler and K. Hartley. Economics of alliances: The lessons for collective action. *Journal of economic literature*, 39(3):869–896, 2001.

[42] W. Schlenker and W. R. Walker. Airports, air pollution, and contemporaneous health. *The Review of Economic Studies*, 83(2):768–809, 2016.

[43] X. Shi, T. Zhibo, and X. Zhang. Air pollution and firm dynamics: the case of chinese manufacturing. *Available at SSRN 4002894*, 2022.

[44] X. Shi, Y. Shen, and R. Song. Living with particles: Disclosure of pollution information, individual responses, and health consequences. *Journal of Health Economics*, 92:102824, 2023.

[45] S. J. Wallace, C. Zepeda-Millán, and M. Jones-Correa. Spatial and temporal proximity: Examining the effects of protests on political attitudes. *American Journal of Political Science*, 58(2):433–448, 2014.

[46] Z. Wang and J. Zhang. The value of information disclosure: Evidence from mask consumption in china. *Journal of Environmental Economics and Management*, 122:102865, 2023.

[47] J. Wei, Z. Li, M. Cribb, W. Huang, W. Xue, L. Sun, J. Guo, Y. Peng, J. Li, A. Lyapustin, et al. Improved 1 km resolution pm 2.5 estimates across china using enhanced space–time extremely randomized trees. *Atmospheric Chemistry and Physics*, 20(6):3273–3289, 2020.

[48] J. Wei, Z. Li, A. Lyapustin, L. Sun, Y. Peng, W. Xue, T. Su, and M. Cribb. Reconstructing 1-km-resolution high-quality pm2. 5 data records from 2000 to 2018 in china: spatiotemporal variations and policy implications. *Remote Sensing of Environment*, 252:112136, 2021.

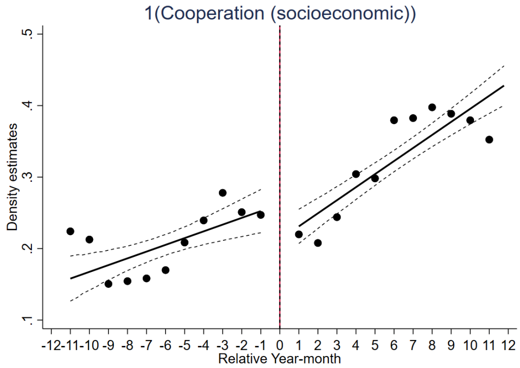
[49] T. Xie, Y. Yuan, and H. Zhang. Information, awareness, and mental health: Evidence from air pollution disclosure in china. *Journal of Environmental Economics and Management*, page 102827, 2023.

[50] X. Zhang, X. Zhang, and X. Chen. Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of environmental economics and management*, 85:81–94, 2017.

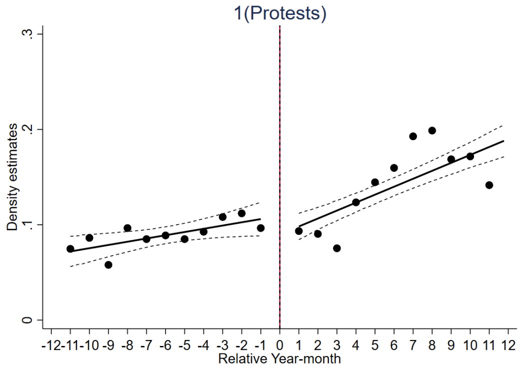
[51] X. Zhang, X. Chen, and X. Zhang. The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences*, 115(37):9193–9197, 2018.

[52] J. G. Zivin and M. Neidell. Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2):119–128, 2009.

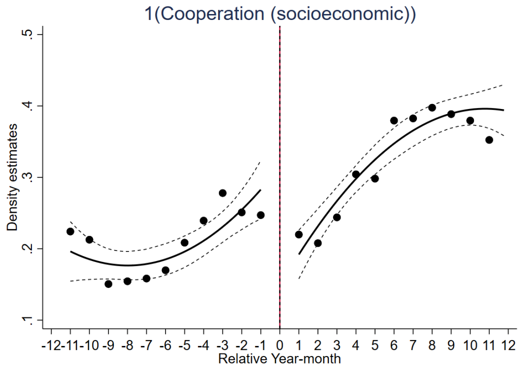
Figure 1: Results of regression discontinuity designs



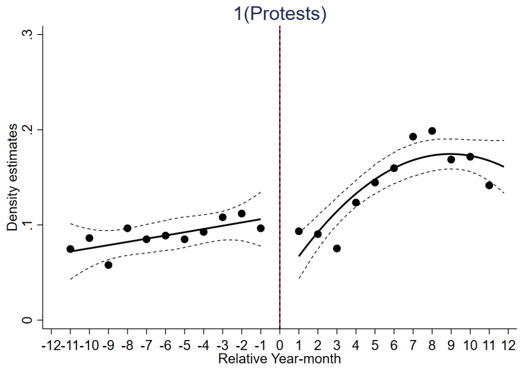
(a)



(b)



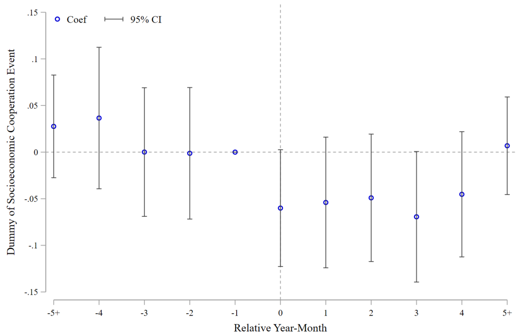
(c)



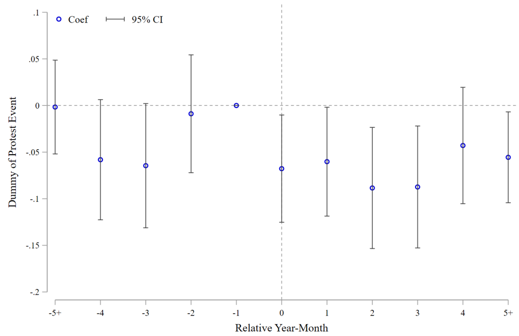
(d)

Notes: The figure illustrates regression discontinuity design. Figures 1(a) and (c) depict the results for 1(Cooperation (socioeconomic)), and Figures 1(b) and (d) depict the results for 1(Protests). Figures 1(a) and (b) use local linear regressions, and (c) and (d) include fourth-order polynomials as controls. The number of bins and the bandwidth are optimally chosen according to Calonico et al. (2019). The relative year-month is the timing of the disclosure policy. 0 is the starting month. We use the same specification as equation (1).

Figure 2: Results of event study designs



(a)



(b)

Notes: The figure illustrates the dynamic effects of the treatment $1(tm = \tau) \times Policy_i$ on various outcomes. The horizontal axis measures the year since the city experienced a treatment. The year-month 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with city fixed effects and year-month fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the negative effect of the information disclosure policy is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment, which is standardized to 0.

Table 1: Baseline results: Regression discontinuity estimation

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Coop. (economic))	1(Coop. (judicial))	1(Protest)
Policy	-0.138*	-0.134*	-0.0244*	-0.517**
	(0.0816)	(0.0715)	(0.0143)	(0.262)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	Y	Y
Observations	7,444	7,444	7,444	7,444
R-squared	0.347	0.301	0.180	0.278

Notes: The sample covers 7,444 city-year-month observations (273 cities and 27 months) from 14 months prior to the treatment and 12 months after the treatment. The bandwidth is optimally chosen according to Calonico et al. (2019). We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table 2: Baseline results: Difference-in-differences estimation

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Protest)	Scale of protest	Coop./Protest
Policy	-0.0413**	-0.0483***	-0.111***	-3.195***
	(0.0163)	(0.0130)	(0.0313)	(0.668)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	20,100	20,100	20,100	20,100
R-squared	0.393	0.313	0.247	0.326

Notes: The sample covers 20,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table 3: Mechanism: The role of the level of air pollution

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))	1(Protest)	Scale of protest	1(Coop. (socioeconomic))	1(Protest)	Scale of prote
Policy	0.00277	-0.0171	-0.0478	0.0208	0.00524	0.00325
	(0.0271)	(0.0182)	(0.0448)	(0.0291)	(0.0182)	(0.0446)
PM2.5	0.000613	0.000200	0.000225			
	(0.000378)	(0.000234)	(0.000604)			
Policy*PM2.5	-0.000912**	-0.000623**	-0.00124**			
	(0.000372)	(0.000250)	(0.000607)			
PM10				0.000506**	0.000190	0.000157
				(0.000201)	(0.000152)	(0.000435)
Policy*PM10				-0.000694***	-0.000579***	-0.00122***
				(0.000236)	(0.000133)	(0.000320)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	19,920	19,920	19,920	19,920	19,920	19,920
R-squared	0.391	0.313	0.248	0.392	0.471	0.616

Notes: The sample covers 19,920 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table 4: Mechanism: Environmental awareness and political attitudes

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop.	(socioeconomic))			1(Protest)	
Policy	1.072***	-0.865***	0.121	0.691***	-0.412***	-0.211**
	(0.394)	(0.221)	(0.208)	(0.212)	(0.137)	(0.106)
Policy*Environmental concerns	-0.181***			-0.120***		
	(0.0635)			(0.0347)		
Policy*Trust in local government		0.163***			0.0728***	
		(0.0442)			(0.0268)	
Policy*Generalized trust			-0.0587			0.0588
			(0.0738)			(0.0375)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	17,100	17,100	17,100	17,100	17,100	17,100
R-squared	0.386	0.387	0.386	0.316	0.316	0.316

Notes: The sample covers 17,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table 5: Mechanism: The role of education

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))				1(Protest)	
Policy	0.174**	0.123**	0.111**	0.0386	-0.00636	0.00224
	(0.0699)	(0.0528)	(0.0502)	(0.0334)	(0.0273)	(0.0296)
Policy*Share of above junior high	-0.401***			-0.151***		
	(0.117)			(0.0558)		
Policy*Share of above high school		-0.797***			-0.179	
		(0.223)			(0.109)	
Policy*Share of above college			-1.404***			-0.416*
			(0.399)			(0.224)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	19,080	19,080	19,080	19,080	19,080	19,080
R-squared	0.385	0.385	0.385	0.287	0.286	0.286

Notes: The sample covers 19,080 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table 6: Mechanism: The role of socioeconomic conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1(Coop. (socioeconomic))					1(Protest)		
Policy	0.659**	-0.223**	0.107*	0.0133	0.206	-0.136**	0.134***	0.0324
	(0.290)	(0.0936)	(0.0619)	(0.0287)	(0.161)	(0.0527)	(0.0474)	(0.0231)
Policy*log(per capita GDP)	-0.0678**				-0.0246			
	(0.0276)				(0.0156)			
Policy*log(Population)		0.0318*				0.0156*		
		(0.0165)				(0.00938)		
Policy*log(mean TFP, OP(ACF))			-0.0263**				-0.0272***	
			(0.0117)				(0.00888)	
Policy*log(mean TFP, LP(ACF))				-0.0218**				-0.0197**
				(0.0109)				(0.00770)
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,520	17,520	7,848	7,848	17,520	17,520	7,848	7,848
R-squared	0.392	0.391	0.387	0.387	0.321	0.321	0.325	0.324

Notes: The sample covers 17,520/7,848 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. The sample sizes are different because the coverage of TFP data is limited. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table 7: Economic implications of public events

	(1)	(2)	(3)
		log(Per capita GDP)	
		IV-2SLS	
log(Coop. (socioeconomic))	0.0434***		
	(0.00616)		
log(Coop. (economic))		0.0436***	
		(0.00570)	
log(Protests)			-0.0366***
			(0.00693)
City FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,131	1,131	1,131
R-squared	0.958	0.958	0.957

Notes: The sample covers 1,131 city-year observations (273 cities and 5 years) from 2013 to 2017. We employ IV-2SLS regressions with fixed effects for all columns, in which the instrument is the treatment variable of air pollution information disclosure. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Online Appendix For Publication

Appendix A Theoretical Framework

A.1 Model

In this section, we develop a model of information disclosure and transmission a la Crawford and Sobel (1982) to rationalize all our hypotheses to be tested.

There is a sender (he) and a receiver (she). The sender is the government that chooses whether to send or disclose information on air pollution, which is denoted as $m \in M$. Suppose that the true level of air pollution is m_0, and the sender can report an arbitrary level of air pollution, taking into account the benefits and the costs of doing so. We assume that m_0 is exogenously determined by nature, and follows a uniform distribution on $[0, 1]$.[A1] The receiver gets the message sent by the government and then chooses whether to initiate socioeconomic cooperation or protest, both, or neither. The strategy of socioeconomic cooperation is a mapping $c(m) : M \to \{0, 1\}$, and the strategy of protest is a mapping $p(m) : M \to \{0, 1\}$. We assume that the strategy can only take values of 0 and 1 since we focus on pure strategy equilibrium. Cooperation and protests incur payoffs to the sender, which is $U_S = c(m) \times u_a + p(m) \times u_b$, where $u_a > 0$ and $u_b < 0$ is the unit payoff incurred by cooperation and protests. Thus, the objective of the sender is to choose optimal information disclosure or the level of $m \in M$.

The receiver has two types, informed (I) and uninformed (U), with the probability of being an informed receiver $P \in [0, 1]$. We regard P as an exogenous parameter that is related to environmental awareness or trust in government. If the public is more aware of the importance of air quality and distrusts the government, then P is larger. The informed receiver can verify the level of air pollution (by checking the reports from the US consulate), and knows the true value of m_0. The uninformed receiver cannot observe m_0, and hence can only have a guess of the true value based on the disclosed information. However, we assume that the uninformed receiver is rational, or fully Bayesian, and forms her belief using Bayes' rule. We denote the belief of the receiver as $E(m^*)$. Specifically, $E(m^*_U)$ is the belief of the uninformed receiver, and $E(m^*_I) \equiv m_0$ is the belief of the informed receiver.

Both the informed and uninformed receiver derive utility from cooperation and protest. We assume that the utility of not engaging in cooperation is a constant -1 (by normalization),[A2] and the utility of engaging in cooperation is a decreasing function of the belief of air pollution $-c_0 \times E(m^*)$, where $c_0 > 1$[A3] is a constant. Such a setting captures the idea of the psychological cost of any productive activity under a high level of perceived air pollution. We assume that the utility of not engaging in protests is 1 (by normalization), and the utility of engaging in protests is an increasing function of information manipulation $p_0 \times (m - E(m^*))^2$, where $p_0 > 1$[A4] is a constant, and $E(m^*)$ is the expectation of m^*.

[A1]The assumption of uniform distribution is required by tractability.

[A2]We can also set the utility to other negative numbers, but at the same time adjust the value of c_0 introduced later.

[A3]We restrict $c_0 > 1$ to create interior solutions.

[A4]We restrict $p_0 > 1$ to create interior solutions.

This setting captures the fact that the receiver will be unhappy and protest if she finds that she is manipulated by the government via misinformation, which is measured by $(m - E(m^*))^2$. Given such a setting, the break-even value of $E(m^*)$ for cooperation is $\frac{1}{c_0}$, and the break-even value of m for protests is $\pm\frac{1}{p_0} + E(m^*)$. The receiver will engage in cooperation if $E(m^*) < \frac{1}{c_0}$, the receiver will engage in protests if $m < -\frac{1}{p_0} + E(m^*)$ or $m > \frac{1}{p_0} + E(m^*)$. We also assume that c_0 and p_0 are the same for both the informed and uninformed receivers.

The game proceeds as follows. At stage 0, nature decides an $m_0 \in M = [0, 1]$. At stage 1, the sender gets the true value of m_0 and sends a message $m \in M$. At stage 2, nature decides whether the receiver is informed with probability P. At stage 3, the receiver receives the message from the sender, forms her belief according to the Bayes' rule, and makes decisions of $c(m) \in \{0, 1\}$ and $p(m) \in \{0, 1\}$. At stage 4, the sender and the receiver get their payoff. Thus, the equilibrium notion we employ is Perfect Bayesian Equilibrium (PBE).

There are many forms of PBEs, but we focus on the following equilibrium configuration. We restrict $M = \{0, 1\}$, and the sender chooses 1 if $m_0 > \bar{m} \in [0, 1]$, chooses 0 if $m_0 < \bar{m}$, indifferent if $m_0 = \bar{m}$. Given such a strategy, the uninformed receiver forms her belief using the Bayes' rule. She believes that $m_0 \in [\bar{m}, 1]$ and follows a uniform distribution when $m = 1$, and $m_0 \in [0, \bar{m}]$ and follows a uniform distribution when $m = 0$. Thus, $E(m_U^*) = \frac{1+\bar{m}}{2}$ when $m = 1$, and $E(m_U^*) = \frac{\bar{m}}{2}$ when $m = 0$. We can thus define the PBE of interest as follows. Note that in this equilibrium, the government does not fully reveal the true value of m_0. We call this equilibrium one that does not involve full information disclosure.

Definition 1. *A PBE without full information disclosure is a tuple* $\{m, E(m_I^*), E(m_U^*), c(m), p(m)\}$, *in which (1)* $m(m_0) : [0, 1] \to \{0, 1\}$ *solves the sender's maximization problem of his expected payoff and takes a cutoff form; (2)* $E(m_I^*) = m_0$ *for the informed receiver and* $E(m_U^*)$ *is formed by Bayes' rule described above for the uninformed receiver; (3)* $c(m)$ *and* $p(m)$ *is determined by maximizing the receiver's payoff using the break-even rule.*

On the other hand, the sender can be mandated to disclose information. Under some exogenous institutional settings in which not disclosing information will incur a sufficiently higher cost to the sender, he has the incentive to fully disclose information. In such an equilibrium, $m \equiv m_0$ and the receiver makes decisions accordingly. The uninformed receiver also believes that $E(m_U^*) = m = m_0$.

We thus have the following propositions. We provide formal proofs in Appendix A.

Proposition 1. *Under some regularity conditions (specified in the proof), information disclosure discourages cooperation and protests.*

Proposition 2. *Information disclosure discourages cooperation and protests more when* m_0 *is larger.*

Proposition 3. *Under some regularity conditions (specified in the proof), information disclosure discourages cooperation and protests more when* P *is larger.*

Proposition 4. *It is uncertain whether the optimal policy for the government is to fully disclose information.*

The above Propositions 1-4 correspond to and rationalize Hypothesis 1-4 one by one.

A.2 Proofs

Proof of Proposition 1: In the equilibrium of full information disclosure, the government will report the true m_0. Thus, for both informed and uninformed receivers, the payoff of not engaging in protests is zero, and thus strictly smaller than that of engaging in protests. As a result, they both will not engage in protests, and thus information disclosure (at least weakly) discourages protests. Next, solve for the optimal strategy of the sender, $\bar{m}$. By the nature of the cutoff strategy, the sender will be indifferent between reporting $m = 0$ and $m = 1$ if $m_0 = \bar{m}$. Note that if under the regularity conditions that $-\frac{1}{p_0} + \bar{m} > 0$, $\frac{1}{p_0} + \bar{m} < 1$, $-\frac{1}{p_0} + \frac{\bar{m}}{2} > 0$, and $\frac{1}{p_0} + \frac{\bar{m}+1}{2} < 1$, then both informed and uninformed receivers will protest. Thus, the sender will make $\frac{\bar{m}+1}{2} < \frac{1}{c_0}$ satisfy and manipulate the uninformed receiver to induce cooperation. However, in the equilibrium of full information disclosure, the uninformed receiver will not engage in cooperation if $m_0 > \frac{1}{c_0}$. Thus, information disclosure discourages cooperation.

□

Proof of Proposition 2: Given the proof of proposition 1, under full information disclosure, the probability of cooperation decreases more if m_0 is larger, given the break-even rule. Also, since the sender has a tendency to manipulate information by reporting $m = 0$, the probability of protests is also larger given a larger m_0. □

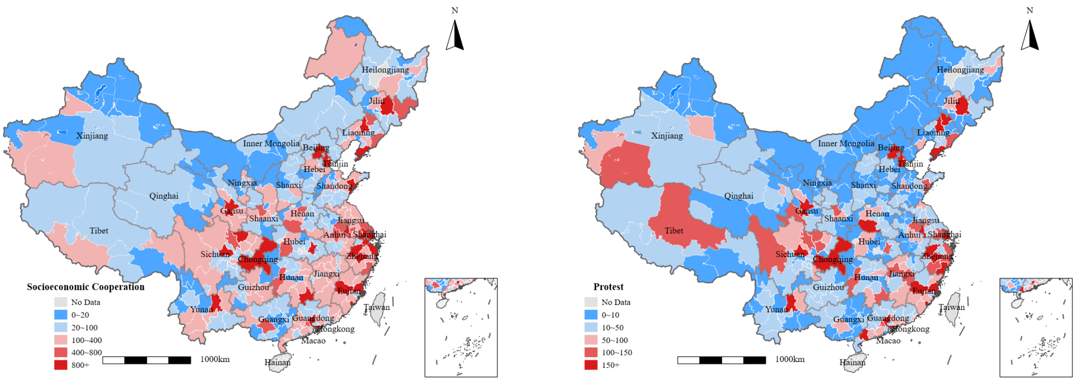
Proof of Proposition 3: The proof starts with the fact that the informed receiver will not be affected by the message sent from the sender. Thus, given a certain level of m_0 that satisfies the regularity conditions that $m_0 < \frac{1}{c_0}$ and $m_0 > \frac{1}{p_0}$, increasing the probability of the informed receiver will raise the probability of both cooperation and protests. Thus, in the equilibrium of full information disclosure, cooperation and protests decrease more.

□

Proof of Proposition 4: The proof follows that of Proposition 1, since information disclosure discourages both cooperation and protests. The welfare effect depends on the relative magnitude of u_a and u_b. □

Appendix B Additional Figures and Tables

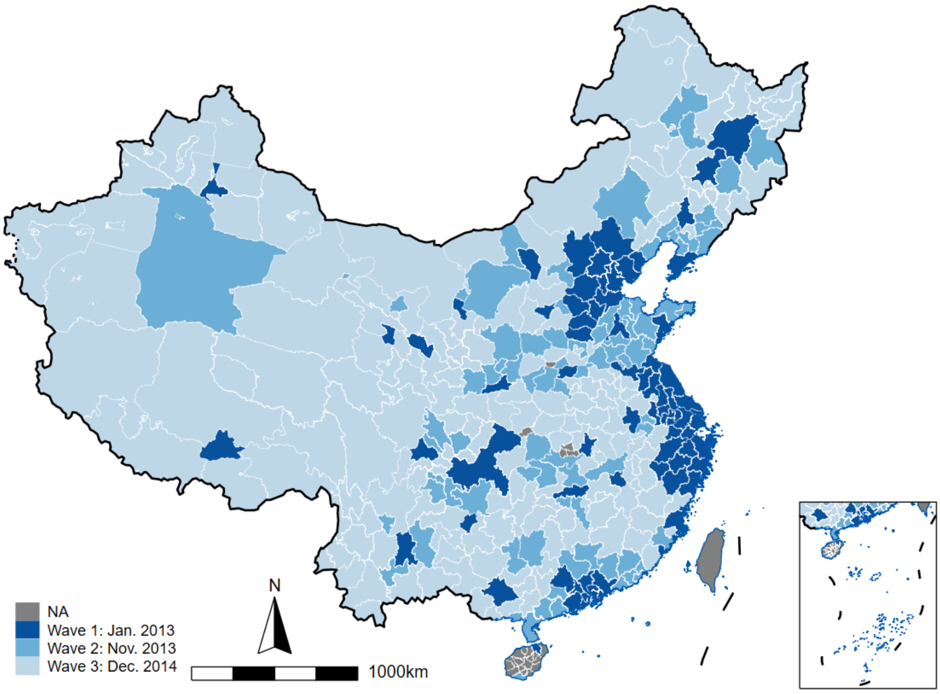
Figure B1: Spatial distribution of public events



(a) (b)

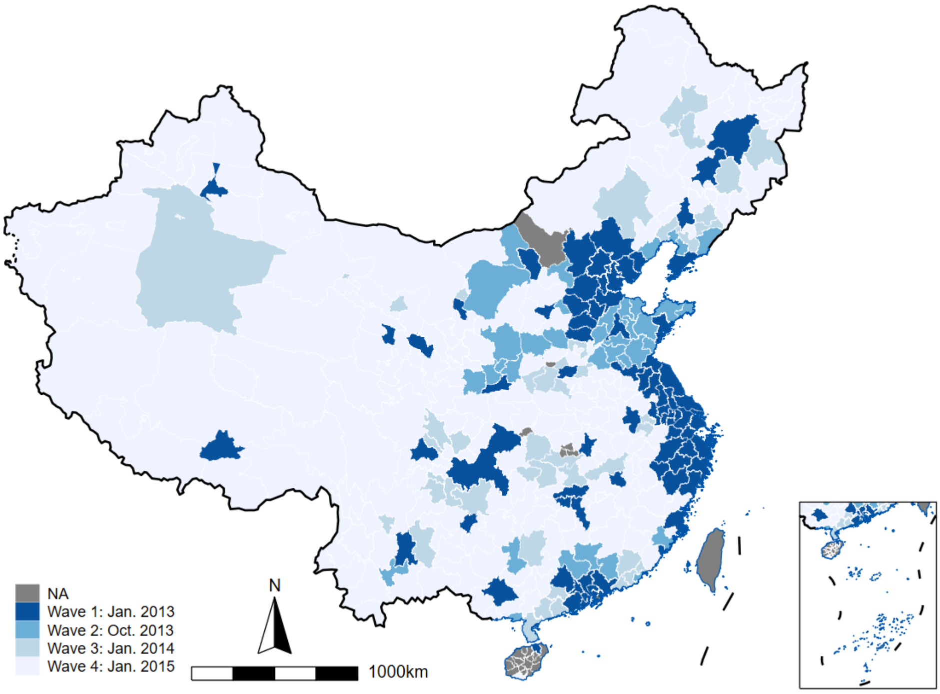
Notes: The figures illustrate the spatial distribution of socioeconomic cooperation and protests.

Figure B2: The map of roll-out planned timings



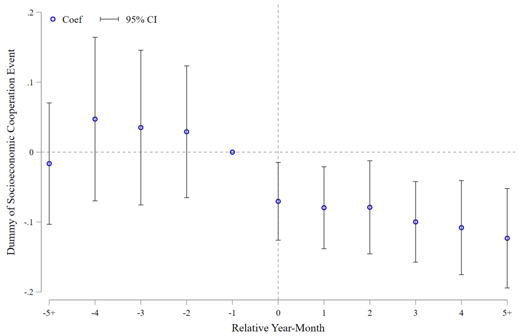
Notes: The figure illustrates the spatial distribution of policy roll-out planned timings.

Figure B3: The map of roll-out implementation timings

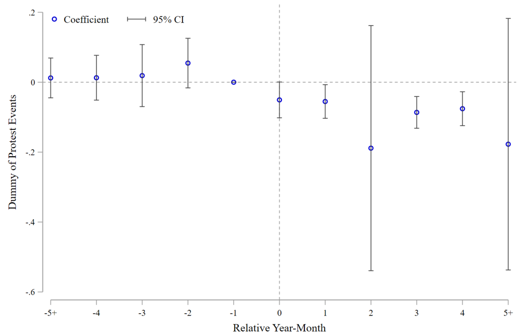


Notes: The figure illustrates the spatial distribution of actual policy roll-out implementation timings.

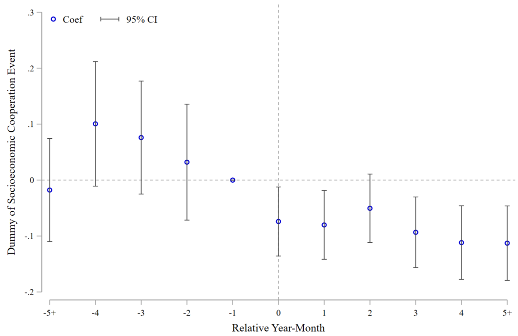
Figure B4: Results of event study designs (De Chaisemartin and d'Haultfoeuille, 2020 and Borusyak et al., 2021)



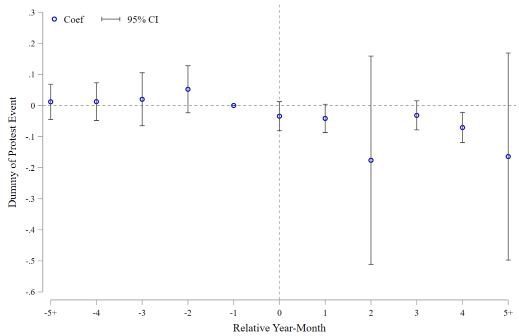
(a)



(b)



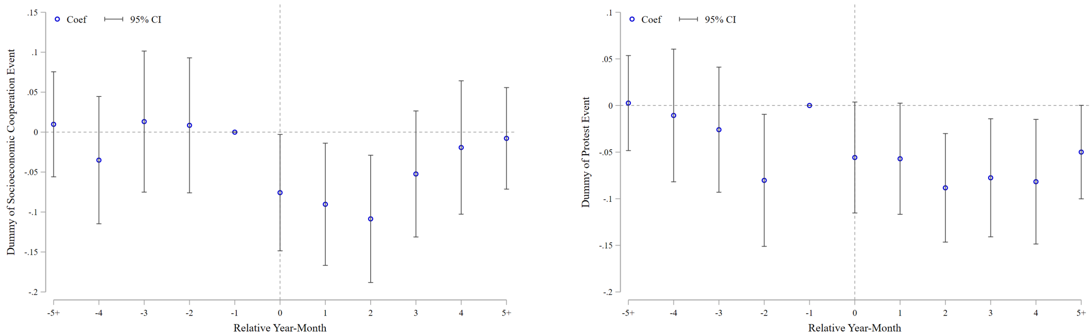
(c)



(d)

Notes: The figure illustrates the dynamic effects of the treatment $1(tm = \tau) \times Policy_i$ on various outcomes. We use the method proposed in De Chaisemartin and d'Haultfoeuille (2020) (subfigures (a) and (b)) and Borusyak et al. (2021) (subfigures (c) and (d)). The horizontal axis measures the year since the city experienced a treatment. The year-month 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with city fixed effects and year-month fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the negative effect of the information disclosure policy is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment, which is standardized to 0.

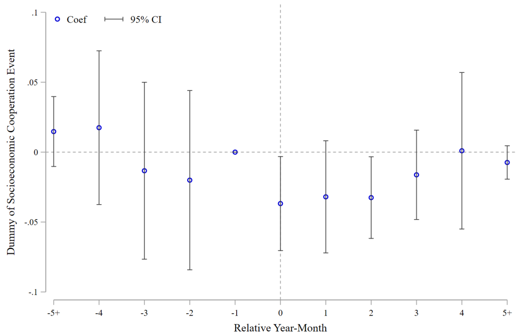
Figure B5: Results of event study designs using implementation timings



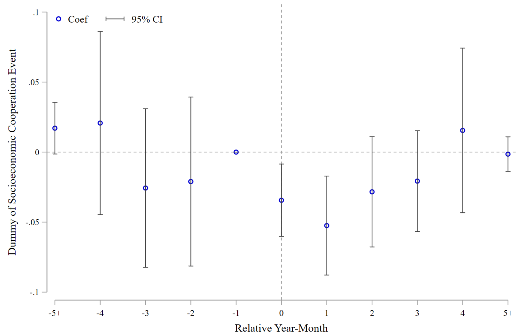
(a) (b)

Notes: The figure illustrates the dynamic effects of the treatment $1(tm = \tau) \times Policy_i$ on various outcomes. The horizontal axis measures the year since the city experienced a treatment. The year-month 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with city fixed effects and year-month fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the negative effect of the information disclosure policy is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment, which is standardized to 0.

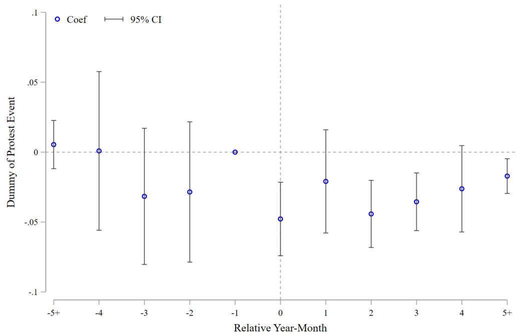
Figure B6: Results of event study designs (interacted with uninstrumented air pollution)



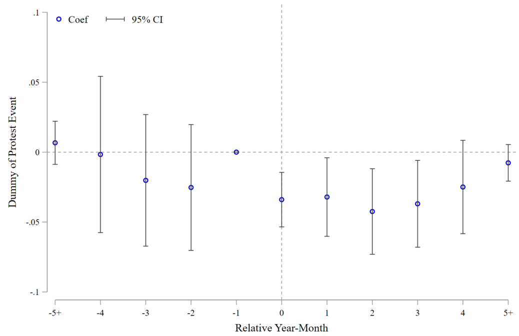
(a)



(b)



(c)



(d)

Notes: The figure illustrates the dynamic effects of the treatment $1(tm = \tau) \times Policy_i \times AirPollution_{i\tau}$ on various outcomes. Figures (a) and (c) correspond to PM10, and Figures (b) and (d) correspond to PM2.5. The horizontal axis measures the year since the city experienced a treatment. The year-month 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with city fixed effects and year-month fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the negative effect of the information disclosure policy is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment, which is standardized to 0.

Table B1: Definition of sub-categories of socioeconomic cooperation

Category	Description	CAMEO Code
Economic	Trade relations and other economic exchanges	61
Judicial	Cooperation on judicial matters, such as extraditions and war crimes	63
Information	Voluntary exchanges or sharing of significant information	64

Notes: The definition is retrieved from Conflict and Mediation Event Observations Event and Actor Codebook. Conflict and Mediation Event Observations (CAMEO) is a framework for coding event data. Socioeconomic cooperation in this paper consists of these three sub-types of cooperation.

Table B2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Coop. (socioeconomic)	20,100	9.629	91.484	0	2785
Coop. (economic)	20,100	4.876	49.136	0	1912
Coop. (judicial)	20,100	0.066	1.732	0	215
Protest	20,100	2.672	37.911	0	2327
1(Coop. (socioeconomic))	20,100	0.378	0.485	0	1
1(Coop. (economic))	20,100	0.246	0.431	0	1
1(Coop. (judicial))	20,100	0.009	0.093	0	1
1(Protest)	20,100	0.158	0.364	0	1
Mean protest scale	20,100	0.366	0.930	0	6
Coop./Protest	20,100	8.147	15.069	0.048	345
PM2.5	19,920	42.438	23.332	6.968	199.301
PM10	19,920	77.166	42.521	15.657	613.441
Mean environmental concerns	17,100	6.212	0.232	5.588	6.992
Mean trust in local government	17,100	5.013	0.291	4.423	5.474

Table B3: Correlations of policy timings

	(1)	(2)	(3)	(4)	(5)	(6)
			Wave			
		OLS			Ordered logistic	
log(SO2)	-0.0435			-0.546*		
	(0.0385)			(0.288)		
log(NO_2)		0.0404			0.149	
		(0.0502)			(0.344)	
log(Dust)			0.0404			0.149
			(0.0502)			(0.344)
log(GDP per capita)	-1.037***	-1.086***	-1.086***	-6.921***	-7.360***	-7.360***
	(0.0930)	(0.0936)	(0.0936)	(0.962)	(0.986)	(0.986)
log(Population)	-0.393***	-0.444***	-0.444***	-2.685***	-3.014***	-3.014***
	(0.0624)	(0.0623)	(0.0623)	(0.601)	(0.585)	(0.585)
Secondary industry share	0.0168***	0.0151***	0.0151***	0.114***	0.105***	0.105***
	(0.00407)	(0.00403)	(0.00403)	(0.0317)	(0.0313)	(0.0313)
Province FE	Y	Y	Y	Y	Y	Y
Observations	279	280	280	279	280	280
R-squared	0.759	0.757	0.757			

Notes: The sample covers 280(279) city observations. Independent variables are from 2012 and are obtained using China's City Statistical Yearbooks. Wave is a discrete variable that takes values of 1, 2, and 3, which corresponds to the first, second, and third wave of roll-out. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B4: Adding controls and additional fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		1(Coop. (socioeconomic))				1(Protest)		
Policy	-0.0412**	-0.0460***	-0.0470***	-0.0399**	-0.0433***	-0.0503***	-0.0509***	-0.0471***
	(0.0178)	(0.0164)	(0.0162)	(0.0165)	(0.0136)	(0.0131)	(0.0131)	(0.0132)
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Economic controls	Y	N	N	N	Y	N	N	N
Climate controls	N	Y	N	N	N	Y	N	N
Air quality controls	N	N	Y	N	N	N	Y	N
City-month FE	N	N	N	Y	N	N	N	Y
Observations	17,520	19,920	19,920	20,090	17,520	19,920	19,920	20,090
R-squared	0.391	0.391	0.391	0.500	0.321	0.313	0.314	0.441

Notes: The sample covers 17,520 (19,920 or 20,100) city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. Economic controls include log per capita GDP, log population, and log number of firms. Climate controls include mean temperature, wind speed, humidity, and sunshine duration. Air quality controls include the levels of PM2.5, PM10, ozone, and NO_2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B5: Correlations between policy timings and attitudes

	(1)	(2)	(3)	(4)
		Wave		
		OLS		
Mean environmental concerns	-1.323***			-1.393***
	(0.249)			(0.269)
Mean trust in local government		0.550**		0.605**
		(0.258)		(0.271)
Mean generalized trust			0.136	0.180
			(0.181)	(0.237)
Province FE	Y	Y	Y	Y
Observations	280	280	280	280
R-squared	0.212	0.139	0.149	0.225

Notes: The sample covers 280 city observations. Independent variables are obtained using CFPS 2012-2018 data. Wave is a discrete variable that takes values of 1, 2, and 3, which corresponds to the first, second, and third wave of roll-out. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B6: Balancing test for regression discontinuity design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean temperature	Wind speed	Relative humidity	Precipitation	Sunshine duration	log(per capita GDP)	GDP growth rate
	Regression discontinuity design (balancing tests)						
Policy	0.125	-0.236	-0.548	32.85	36.33	6.63e-05	-0.0134
	(0.971)	(0.219)	(5.144)	(61.24)	(28.93)	(0.00314)	(0.0446)
City FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	Y	Y	Y	Y	Y
Observations	6,116	6,116	6,116	6,116	6,116	5,201	4,994
R-squared	0.930	0.822	0.752	0.606	0.671	0.995	0.580

Notes: The total sample covers 6,116 city-year-month observations (273 cities and 27 months) from 14 months prior to the treatment and 12 months after the treatment. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B7: Robustness checks for regression discontinuity design

Panel A: Alternative bandwidths								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)
	[-16,14]		[-14,14]		[-14,12]		[-12,12]	
Policy	-0.204***	-0.0617**	-0.173***	-0.0469*	-0.152**	-0.0164	-0.170***	-0.0336
	(0.0446)	(0.0289)	(0.0427)	(0.0279)	(0.0624)	(0.0394)	(0.0613)	(0.0378)
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8,456	8,456	8,108	8,108	7,444	7,444	7,096	7,096
R-squared	0.242	0.188	0.238	0.185	0.247	0.193	0.245	0.192

Panel B: Alternative orders of polynomial						
	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)
	Third-order		Second-order		First-order	
Policy	-0.323***	-0.0876**	-0.253***	-0.0876**	-0.232***	-0.0897***
	(0.0601)	(0.0364)	(0.0468)	(0.0364)	(0.0395)	(0.0266)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
High-order polynomial	Y	Y	Y	Y	Y	Y
Observations	7,444	7,444	7,444	7,444	7,444	7,444
R-squared	0.245	0.192	0.244	0.192	0.244	0.192

Notes: In Panel A, the total sample covers 273 cities and various months according to different bandwidths. In Panel B, the total sample covers 7,444 city-year-month observations (273 cities and 27 months) from 14 months prior to the treatment and 12 months after the treatment. We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B8: The role of the level of air pollution: IV-2SLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))	1(Protest)	Scale of protest	1(Coop. (socioeconomic))	1(Protest)	Scale of protest
	IV-2SLS					
Policy	17.68***	8.668**	18.38*	1.647***	0.782**	1.651
	(6.043)	(3.911)	(10.89)	(0.578)	(0.373)	(1.039)
PM2.5	0.304**	0.286***	0.754***			
	(0.121)	(0.0765)	(0.234)			
Policy*PM2.5	-0.418***	-0.205**	-0.436*			
	(0.142)	(0.0922)	(0.257)			
PM10				0.0160**	0.0150***	0.0395***
				(0.00633)	(0.00402)	(0.0123)
Policy*PM10				-0.0219***	-0.0108**	-0.0229*
				(0.00747)	(0.00484)	(0.0135)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	19,920	19,920	19,920	19,920	19,920	19,920
R-squared	0.391	0.313	0.248	0.391	0.313	0.248

Notes: The sample covers 19,920 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. The instrumental variable for PM2.5 and PM10 is the number of thermal inversions during the same time period. The F-statistic for PM2.5 is 119.88, and the F-statistic for PM10 is 144.66. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at various levels.

Table B9: Robustness checks using the timing of implementation

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Protest)	1(Coop. (socioeconomic))	1(Protest)
	Regression discontinuity design		Difference-in-differences design	
Policy (implementation)	-0.131*	-0.133**	-0.0369**	-0.0490***
	(0.0766)	(0.0630)	(0.0160)	(0.0126)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	N/A	N/A
Observations	7,444	7,444	20,100	20,100
R-squared	0.351	0.283	0.393	0.313

Notes: In columns (1) and (2), the sample covers 7,444 city-year-month observations (273 cities and 27 months) from 14 months prior to the treatment and 12 months after the treatment. In columns (3) and (4), the sample covers 20,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B10: Counts and log transformations: Regression discontinuity estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Coop. (socioeconomic))	arcsinh(Coop. (socioeconomic))	log(1+Protests)	arcsinh(Protests)	Coop. (socioeconomic)	Protests
Policy	-0.374**	-0.287**	-1.169*	-0.751	-23.823*	-4.299
	(0.166)	(0.130)	(0.703)	(0.489)	(13.780)	(3.178)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	Y	Y	Y	Y
Observations	7,444	7,444	7,444	7,444	7,444	7,444
R-squared	0.512	0.546	0.364	0.384	0.364	0.384

Notes: The sample covers 7,444 city-year-month observations (273 cities and 27 months) from 14 months prior to the treatment and 12 months after the treatment. We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B11: Counts and log transformation: Difference-in-differences estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Coop. (socioeconomic))	arcsinh(Coop. (socioeconomic))	log(1+Protests)	arcsinh(Protests)	Coop. (socioeconomic)	Protest
Policy	-0.251***	-0.217***	-0.103***	-0.0708***	-10.42*	-1.902
	(0.0448)	(0.0378)	(0.0286)	(0.0218)	(6.262)	(1.504)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	20,100	20,100	20,100	20,100	20,100	20,100
R-squared	0.617	0.658	0.527	0.593	0.864	0.746

Notes: The sample covers 20,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B12: Alternative ways of clustering standard errors

	(1)	(2)
	1(Coop. (socioeconomic))	1(Protest)
Policy	-0.0413	-0.0483
Robust standard error	(0.0112)***	(0.00935)***
Two-way clustered at city and year levels	(0.0118)**	(0.0184)**
Two-way clustered at city and month levels	(0.0222)*	(0.0194)**
Two-way clustered at city and year-month levels	(0.0119)**	(0.0182)**
City FE	Y	Y
Year-month FE	Y	Y
Observations	20,100	20,100
R-squared	0.393	0.313

Notes: The sample covers 20,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at various levels.

Table B13: Accounting for regional spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))	Coop. (socioeconomic)	Protests	1(Protests)	Scale of protest	Coop./Protests
Policy	-0.0242*	-2.640***	-0.137	-0.0353**	-0.0885**	-3.443***
	(0.0150)	(0.729)	(0.189)	(0.0149)	(0.0364)	(0.804)
Mean policy in neighbors	-0.0578*	-0.382	-0.129	-0.0270	-0.0434	0.730
	(0.0294)	(1.285)	(0.362)	(0.0269)	(0.0662)	(1.463)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	19,860	19,860	19,860	19,860	19,860	19,860
R-squared	0.382	0.561	0.282	0.282	0.222	0.320

Notes: The sample covers 19,860 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The standard errors are clustered at the city level.

Table B14: Drop the first one to three days of each month

	(1)	(2)	(3)
	1(Coop. (socioeconomic))	1(Protests)	Scale of protest
Policy	-0.0459**	-0.0454***	-0.110***
	(0.0182)	(0.0141)	(0.0330)
City FE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	20,100	20,100	20,100
R-squared	0.380	0.292	0.230

Notes: The sample covers 20,100 city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B15: Baseline results with daily data

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	Regression discontinuity design		Difference-in-differences design	
Policy	-0.219**	-0.151*	-0.0321*	-0.0281**
	(0.0991)	(0.0932)	(0.0179)	(0.0142)
City FE	Y	Y	Y	Y
Year-month-day FE	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	N/A	N/A
Observations	215,650	215,650	608,909	608,909
R-squared	0.132	0.148	0.134	0.221

Notes: In columns (1) and (2), the sample covers 215,650 city-year-month-day observations (273 cities and 27 months) from 14 months before the treatment and 12 months after the treatment. In columns (3) and (4), the sample covers 608,909 city-year-month-day observations (273 cities and 5 years) from January 1st, 2013 to December 31st, 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B16: Baseline results with weekly data

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	Regression discontinuity design		Difference-in-differences design	
Policy	-0.140*	-0.0268*	-0.0515**	-0.0376**
	(0.0811)	(0.0171)	(0.0199)	(0.0159)
City FE	Y	Y	Y	Y
Year-month-day FE	Y	Y	Y	Y
Time fourth-order polynomial	Y	Y	N/A	N/A
Observations	47,302	47,302	140,719	140,719
R-squared	0.159	0.169	0.165	0.196

Notes: In columns (1) and (2), the sample covers 47,302 city-year-month-week observations (273 cities and 27 months) from 14 months before the treatment and 12 months after the treatment. In columns (3) and (4), the sample covers 140,719 city-year-month-week observations (273 cities and 5 years) from January 1st, 2013 to December 31st, 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B17: Addressing data quality issues

	(1)	(2)
	Total data points	
	RD design	DID design
Policy	-54.79	-32.82
	(37.83)	(32.54)
City FE	Y	Y
Year-month FE	Y	Y
Time fourth-order polynomial	Y	N
Observations	7,444	20,100
R-squared	0.673	0.779

Notes: In column (1), the sample covers 7,444 city-year-month-week observations (273 cities and 27 months) from 14 months before the treatment and 12 months after the treatment. In column (2), The sample covers 20,100 city-year-month-week observations (273 cities and 5 years) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B18: Regional heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	North China		Northeast		East China	
Policy	0.00876	-0.0239	-0.0846*	-0.0757*	-0.0507	-0.0737***
	(0.0514)	(0.0263)	(0.0421)	(0.0402)	(0.0329)	(0.0279)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	2,160	2,160	2,100	2,100	4,620	4,620
R-squared	0.349	0.419	0.415	0.412	0.422	0.313
	(7)	(8)	(9)	(10)	(11)	(12)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	South China		Southwest		Northwest	
Policy	-0.104***	-0.0271	0.0586	-0.0210	-0.0718*	-0.0838***
	(0.0290)	(0.0280)	(0.0427)	(0.0412)	(0.0394)	(0.0293)
City FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Observations	4,740	4,740	3,240	3,240	3,060	3,060
R-squared	0.366	0.282	0.350	0.284	0.386	0.281

Notes: The sample covers 20,100 (in total of all regions) city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. We employ OLS regressions with fixed effects for all columns. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Table B19: Seasonal heterogeneity

	(1)	(2)	(3)	(4)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	Spring		Summer	
Policy	-0.0767***	-0.102***	-0.0207	-0.0277
	(0.0266)	(0.0222)	(0.0254)	(0.0213)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	5,025	5,025	5,025	5,025
R-squared	0.424	0.356	0.421	0.357

	(5)	(6)	(7)	(8)
	1(Coop. (socioeconomic))	1(Protests)	1(Coop. (socioeconomic))	1(Protests)
	Fall		Winter	
Policy	0.0153	0.00546	-0.0778***	-0.0676***
	(0.0264)	(0.0228)	(0.0244)	(0.0207)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	5,025	5,025	5,025	5,025
R-squared	0.422	0.338	0.422	0.350

Notes: The sample covers 20,100 (in total of all seasons) city-year-month observations (273 cities and 60 months) from January 2013 to December 2017. Variable "Wave" takes three values, 1, 2, and 3, which correspond to each wave of timings. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the city level.

Appendices Not For Publication

Appendix C Data Appendix

C.1 Air Pollution Data

The concentrations of PM2.5 pollution were obtained from the China High Air Pollutants (CHAP) dataset, which was developed by Wei et al. (2020, 2021). The dataset utilizes artificial intelligence technology, with solar radiation intensity and air temperature as the primary predictors, combined with ground-based observations, atmospheric reanalysis, emission inventories, and other big data sources to generate a seamless daily PM2.5 concentration dataset spanning from 2000 to 2020. The spatial resolution is set at 1 kilometer, and we derive the mean values across all grids for each city.

C.2 Thermal Inversion Data

For the instrumental variable, we obtain thermal inversion data from the product M2I6NPANA, version 5.12.4, released by NASA. The data report air temperatures every six hours for each $0.5^{\circ} \times 0.625^{\circ}$ (around 50 km $\times$ 60 km) grid, for 42 layers, ranging from 110 meters to 36,000 meters. We extract the mean values for each city in China. For every six-hour period, we further derive the temperature difference between the second layer (320 meters) and the first layer (110 meters). Under normal conditions, the difference would be negative. Thermal inversion occurs when the temperature difference is positive. We define a daily thermal inversion as a positive temperature difference observed during any six-hour period throughout the day.

C.3 Population Census Data

In the paper, we use 2005 Chinese Population Census data to provide an examination of possible mechanisms. The 2005 Chinese population census was a significant national survey conducted by the National Bureau of Statistics of China. It provides information including the number of population, age structure, and educational attainments at the individual level. The 2005 Chinese Population Census was a comprehensive survey, and the collected data played a crucial role in informing the government's policies and plans for social and economic development.

Appendix D Case Studies

In this section, we provide several cases of socioeconomic cooperation and protests. We would like to emphasize the fact that the incentives to engage in cooperation are dampened when there is a higher level of air pollution that causes discomfort.

The first case of cooperation is an appeal for agricultural cooperation with Australia initiated by Shenzhen City, Guangdong Province.[D1] Guangdong Province, home to over 100 million people, consumes approximately 12 million tonnes of grains annually. However, the total demand for cereals is much higher, roughly double, due to the need to feed livestock and for other industrial uses. This creates an opportunity for cooperation with Australia, which exports about 26 million tonnes of grain each year, sufficient to meet Guangdong's entire demand. Consequently, in June 2014, Shenzhen City signed a cooperation contract with Australia for the trade and production of cereal and grain products.

The second case of cooperation is an appeal for agricultural trade expansion with Russia.[D2] In 2013, Chinese companies exported $2.1 billion worth of agricultural products to Russia. China is prepared to enhance its collaboration with Russia to boost bilateral trade in agricultural products. Specifically, China aims to strengthen its economic and trade relations with Russia and will continue to create favorable conditions for bilateral cooperation in the energy and agricultural sectors, as well as in infrastructure and technology. Consequently, China signed a cooperative agreement with Russia in Beijing in August 2014.

We also provide two cases of protests. The first one is a protest that happened in Kardze prefecture of Sichuan province against the authority in August 2014 since they refused to treat detained Tibetans with gunshot wounds.[D3] On August 12, 2014, Chinese police opened fire and detained numerous Tibetans while dispersing a mass protest. The protest erupted in response to the arrest of a respected leader in Kardze's Shopa village in Sershul (Shiqu) county the previous day. The village leader, Dema Wangdak, had been detained after voicing complaints to authorities about the harassment of Tibetan women by senior Chinese officials during a cultural performance during their visit to the county.

The second one is a protest that happened in August 2014 in Beijing in support of democracy in Hong Kong.[D4] Tens of thousands of people marched in protest against a planned civil disobedience campaign by pro-democracy activists demanding electoral reform. The demonstration faced criticism as another step by Beijing to interfere in Hong Kong politics. Demonstrators, many wearing red and waving Chinese flags, endured the sweltering heat to participate in the rally on Sunday afternoon. Organized by a pro-Beijing group, the rally aimed to outdo a July 1 pro-democracy march and undermine the Occupy Central movement. The Occupy Central movement has threatened to paralyze the central business

---

[D1] For a news report, see `https://www.smh.com.au/business/china-looks-to-australia-to-satisfy-growing-grain-appetite-20140729-zxx2r.html`.

[D2] For a news report, see `https://sputnikglobe.com/20140818/China-Ready-to-Expand-Agricultural-Trade-With-Russia-192121328.html`.

[D3] For a news report, see `https://www.rfa.org/english/news/tibet/gunshot-08182014014610.html`.

[D4] For a news report, see `https://www.theage.com.au/world/probeijing-demonstration-shows-battle-for-hong-kong-on-in-earnest-20140818-105fod.html`.

district of Asia's biggest financial center if China's proposal for electing Hong Kong's chief executive in 2017 fails to meet international standards.