Journal of Environmental Economics and Management 115 (2022) 102724

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Air pollution and political trust in local government: Evidence from China☆

Yao Yao [a,b], Xue Li [a], Russell Smyth [c], Lin Zhang [d,*]

[a] School of International Economics and Trade, Shanghai Lixin University of Accounting and Finance, Shanghai, China
[b] School of Economics & Finance, Curtin Business School, Curtin University, Perth, WA, Australia
[c] Monash Business School, Monash University, Melbourne, VIC, Australia
[d] School of Energy and Environment, City University of Hong Kong, Hong Kong Special Administrative Region

ARTICLE INFO

Keywords:
Air pollution
$PM_{2.5}$
Political trust
Local government
China
CFPS
JEL classification: Q01
Q56
Q58

ABSTRACT

While it is well-established that air pollution damages health and inhibits productivity, the political cost of air pollution remains poorly understood. We estimate the causal effect of air pollution on political trust in local government in China, which underpins the stability of the authoritarian state. Combining a nationally representative longitudinal survey with satellite derived $PM_{2.5}$ concentrations, we find that a one μg/m^3 exogenous increase in $PM_{2.5}$ concentrations, due to atmospheric thermal inversion, reduces trust in local government by 4.1 per cent of one standard deviation. This implies that if China were to reduce $PM_{2.5}$ emissions to the annual standard of 35 μg/m^3 mandated by the Chinese government, this would boost trust in local government by 21.2 per cent evaluated at the mean. We examine the underlying transmission channels and find that prolonged exposure to $PM_{2.5}$ lowers citizens' life satisfaction and evaluation of local government performance, induces adverse health effects, imposes additional financial burden and, albeit to a lesser extent, reduces household income.

1. Introduction

That air pollution lowers social welfare has been well established across a broad range of disciplines. Research in economics demonstrates that exposure to air pollution can have adverse effects on infant health (Greenstone and Hanna, 2014; Knittel et al., 2016; Jones, 2020), cognitive performance (Ebenstein et al., 2016; Graff Zivin et al., 2020) and labor supply and productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; He et al., 2019; Chang et al., 2016, 2019). More recently, air pollution has been linked to higher rates of obesity (Deschenes et al., 2020), sleep deprivation (Heyes and Zhu, 2019) and aggressive behaviors (Sager 2019; Bondy et al., 2020; Herrnstadt et al., 2021), to name a few.

One area that has received surprisingly little attention is how air pollution affects citizens' trust in government. In general, political

☆ We thank the editor and three anonymous referees for their valuable comments and suggestions. Yao Yao acknowledges the financial support from Shanghai Sailing Project by Shanghai Science and Technology Committee (Grant No. 20YF1434100), Shanghai Eastern Young Scholar program (Grant No. QD20200046). Lin Zhang gratefully acknowledges financial support from the Department of Science and Technology of Sichuan Province (Grant No. 2021JDR0180).

* Corresponding author.
E-mail addresses: ethan.yaoyao@outlook.com (Y. Yao), lixue1207lixin@163.com (X. Li), russell.smyth@monash.edu (R. Smyth), l.zhang@cityu.edu.hk (L. Zhang).

https://doi.org/10.1016/j.jeem.2022.102724
Received 24 November 2021; Received in revised form 8 April 2022; Accepted 15 August 2022
Available online 26 August 2022
0095-0696/© 2022 Elsevier Inc. All rights reserved.

trust refers to citizens' beliefs that the government is established for improving their welfare. It underpins political support and regime legitimacy, particularly during periods of unexpected downturns (Easton, 1965). While government may be able to sidestep poorer than expected responses to natural disasters, prolonged exposure to air pollution is due, in large part, to lax or weakly enforced environmental standards. This link makes it relatively straightforward for the public to establish a connection between poor governance and air pollution, which imposes substantial economic and health burdens on citizens. To avoid air pollution, citizens may have to cancel outdoor activities and displace utility-generating consumption with costly defensive investment (Deschenes et al., 2017; Ito and Zhang, 2020). It results in huge welfare losses, which have the potential to spark public discontent. Protests about the effects of air pollution have been proliferating globally, fueled by citizens' growing environmental awareness and ease of organizing protest via the internet and mobile phones (Pargal and Wheeler, 1996; Wang, 2013; Greenstone and Hanna, 2014).

In this study, we estimate the causal effect of air pollution on political trust in local government in China. China is ruled by an authoritarian regime and much of its political support is derived from robust economic success. Thus, in the Chinese context, when we say that political trust refers to people's beliefs that the government exists for improving their welfare, we are referring specifically to economic welfare, rather than a broader notion of welfare that includes cultural or political freedoms. The justification for employing this more narrow definition of political trust is that it is consistent with the argument many have made that the Chinese government draws its legitimacy by improving the economic welfare of its citizens (see eg. Guo, 2009). However, as noted by Ebenstein et al. (2015), the benefits of high economic growth have been increasingly offset by the cost of environmental degradation, which implies that the regime may struggle to garner support in the future.

The Chinese context provides an ideal setting for studying the relationship between air pollution and trust in local government for several reasons. First, local officials in China are evaluated by upper-level government rather than by citizens within their jurisdictions. Officials in this setting are arguably less accountable to local citizens, allowing public discontent to grow and evolve into lower political trust.[1] Second, in contrast to most western democracies, political trust in China is hierarchical in that most citizens exhibit higher level of trust in central government than in local government (Chen, 2017; Dong and Kübler, 2018).[2] However, virtually all policies are implemented at the local level, meaning that trust in local government is imperative to ensure the efficient functioning of the regime. Finally, air pollution has become highly politicized in China as a major concern of the central government, especially after severe smog blanketed much of China in the early 2010s. Several national-level pieces of legislation, including the landmark 2013 Action Plan on Prevention and Control of Air Pollution, were promulgated to improve air quality. However, local responses to addressing air pollution varied considerably across counties. In contrast to mass incidents related to sensitive issues, such as human rights or free elections, protests about air pollution, which are directed towards local government, are tolerated by the central government, because they help increase local compliance with environmental legislation (Wang, 2013). This context provides us with a rare opportunity to estimate the effect of air pollution on political trust in local government.

In terms of whether our findings have external validity, we argue that China's case is representative of many other authoritarian states and states with fragile democracies that, like China, garner public support, and ultimately, regime legitimacy from promoting economic growth (see eg. Nathan, 2020). However, pursuing a growth-based regime survival strategy might have unintended consequences, such as environmental degradation, which, in turn, adversely affect trust in the regime. This concern is magnified by growing environmental awareness as well as the lower costs of acquiring information about environmental degradation and the ease of organizing social assembly. For states with nascent democracies, political trust is perhaps even more critical, as it is a prerequisite for deep democratic reforms.

We use China Family Panel Studies (CFPS), a nationally representative and longitudinal survey, which tracks political trust of 33,600 adults biennially from 2012 to 2018. Since respondents may be less willing to reveal their true trust in government under an authoritarian regime, we carry out several checks to reduce the likelihood that self-censorship biasing our results. We then match the CFPS dataset with monthly $PM_{2.5}$ concentrations according to the county of residence and month of the interview for each respondent.[3] To calculate monthly $PM_{2.5}$ concentrations, we use a satellite dataset produced by fitting aerosol optical depth (AOD) retrievals with a chemical transport model and proxy it to individual-level $PM_{2.5}$ exposure.

Identifying the casual effect of air pollution on political trust has two challenges. The first is omitted variable bias. While the survey's panel structure allows us to control for individual fixed effects, there are unobserved and time-varying confounding factors that can potentially bias OLS estimates. The other challenge is that our satellite based $PM_{2.5}$ dataset contains measurement error.

To address these two challenges, we instrument for local $PM_{2.5}$ concentrations with atmospheric thermal inversions. Air temperature usually decreases with altitude, allowing air pollutants to rise and disperse. However, when thermal inversions occur, the temperature in the upper atmospheric layer is higher than that in the lower layer, thereby trapping air pollution at the surface. The formation of thermal inversions is a complex atmospheric phenomenon and is typically independent of factors that could influence political trust. The causal effect of air pollution on political trust is identified through exploiting the exogenous variations in $PM_{2.5}$, which are due to thermal inversions, across different CFPS waves for the same respondent. To address seasonality in local environmental and economic conditions, we flexibly control for weather variables and include fixed effects at individual and county-year levels.

The baseline estimate suggests that a one $\mu g/m^3$ increase in mean $PM_{2.5}$ concentrations reduces political trust by 0.106 units, which is equivalent to 4.1 per cent of one standard deviation. This finding implies that air pollution has imposed a large political cost on local

[1] In Online, Appendix A we provide information on how local officials are appointed and evaluated.

[2] A commonly held belief in China is that the central government's policies are good, but local government implements central policies selectively and, sometimes, poorly.

[3] The county locations are confidential. One can apply for the restricted information through the online application portal: http://www.isss.pku.edu.cn/cfps/sjzx/xzsj/index.htm?CSRFT=DL2A-N421-HSBD-92CV-JN5B-1B1Q-3RVA-5N9G.

government, which is consistent with the growing willingness-to-pay (WTP) for clean air in China (Zhang et al., 2017; Zhang and Mu, 2018; Freeman et al., 2019; Ito and Zhang, 2020).

Our baseline result is robust to numerous checks. Excluding respondents who have intrinsically weak or strong political trust does not qualitatively change the estimates. More importantly, the documented effect is unique to trust in local government and is not evident for trust in parents, physicians, or Americans, suggesting that unobservables are unlikely to be driving our findings. Moreover, controlling for general trust, such as trust in strangers or neighbors, only marginally alters the estimates, ruling out the possibility that our finding is due to changes in general trust. Our baseline result is also robust to other checks, such as using official $PM_{2.5}$ data from ground monitors, an alternative instrument based on thermal inversion strength as well as a set of different model specifications and clustering strategies.

Leveraging the rich information from CFPS, we examine direct and indirect mechanisms through which air pollution may influence trust in local government. We find that prolonged exposure to higher $PM_{2.5}$ concentration raises respondents' concerns about environmental quality and, more crucially, lowers their life satisfaction and approval rating of local government performance. We find that prolonged exposure to higher $PM_{2.5}$ concentrations significantly worsens respondents' health, measured by both self-reported health status and physician-diagnosed chronic diseases. These negative health outcomes are likely to impose additional stress on healthcare, which crowds out consumption and reduce respondents' welfare. We find that a one $\mu g/m^3$ increase in mean $PM_{2.5}$ concentrations leads to a 1.84 per cent increase in out-of-pocket medical expenditure, a standard measure that captures patients' financial burden. Moreover, we also find suggestive evidence that higher $PM_{2.5}$ concentrations reduces household income, which broadly underpins political support in China.

We contribute to related literature in several important ways. First and foremost, we are the first to examine the causal effect of air pollution on political trust. The only related study, of which we are aware, is Alkon and Wang (2018), who estimate the causal effect of air pollution in Beijing on local citizens' satisfaction with government. Exploiting the exogeneous reduction in daily air pollution due to preparing for a high-stakes public event – a military parade in Beijing – those authors find that a one unit increase in the air quality index (AQI) reduces satisfaction with local government by 0.065 units. We differ from their study in that we focus on trust in local government, a concept with more profound implications for local governance. While satisfaction with government is correlated with political trust, the latter is shown to be persistent due to its historical origins, and, therefore, is arguably more difficult to manipulate (Malmendier and Nagel, 2011; Nunn and Wantchekon, 2011; Chen and Yang, 2019). Our longitudinal survey also examines trust in government for a representative sample for China as a whole, not just Beijing, and over almost a decade. The much longer time span enables us to uncover prolonged, rather than temporal, effects from exposure to air pollution. Methodologically, we exploit an external instrument, thermal inversions, a ubiquitous atmospheric phenomenon, to isolate the exogeneous variations in air pollution across China.

Second, our contribution is related to the growing literature on what determines trust in institutions. Much of the work in this area has focused on rare historical shocks and how they have shaped trust levels in modern times. For example, Nunn and Wantchekon (2011) show that differences in trust in local councils in Africa can be traced back to the Transatlantic and Indian Ocean slave trade over 400 years ago. Malmendier and Nagel (2011) find that individuals who grew up during the Great Depression exhibit lower trust in financial institutions. Chen and Yang (2019) show that the Chinese Great Famine reduced people's trust in local government. While those historical shocks provide credible sources for identification, they may be of limited value in formulating policy responses and, hence, raise concerns about generalizability (Almond et al., 2014). We extend this literature to examine the effect of air pollution, an important and ongoing political issue, on the formation of political trust.

Third, previous studies have shown that air pollution can trigger short-term emotional responses. Examples include aggressive behavior, such as violent crime (Bondy et al., 2020; Burkhardt et al., 2019; Herrnstadt et al., 2021) or dangerous driving (Sager, 2019), and making emotional decisions, related to health insurance (Chang et al., 2018), property transactions (Qin et al., 2019) and financial forecasting (Dong et al., 2019). However, the connection has not been established between air pollution and long-term outcomes. For example, existing studies have shown that air pollution triggers short-lived depressive symptoms, but has no effect on long-term oriented life satisfaction (Zhang et al., 2017). We extend the literature on the psychological effects of air pollution beyond showing it has short-term emotional impulses to demonstrate that higher levels of pollution cause lower levels of trust, which is a more persistent domain with a cognitive basis (Nunn and Wantchekon, 2011; Chen and Yang, 2019). Unlike emotional responses to the effects of air pollution, political trust takes time to be restored and losing it may generate long-lasting social costs (Chen and Yang, 2019).

Finally, we complement the small, but growing, literature on what motivates local officials in China to adopt more stringent environmental standards. Existing studies have adopted a top-down perspective, focusing on the role of local officials' promotion, as the major factor driving environmental progress (Kahn et al., 2015; Chen et al., 2018; He et al., 2020a, 2020b; Wu and Cao, 2021). However, this framework overlooks the role played by the preferences of local citizens for environmental amenities. It also neglects the fact that the central government has increasingly relied on public supervision to strengthen local environmental management (Wang, 2013). While our study does not explicitly address the association between environmental quality and political promotion, we provide novel evidence that air pollution can undermine political trust, an essential input to public governance, which, in turn, affects local officials' performance and eventually their prospects of being promoted. Using manually collected data that tracks the political careers of local officials in China, we empirically show that lower political trust, indeed, reduces their chance of being promoted.

2. Air pollution, institutions, and mechanisms

2.1. Air pollution and environmental governance

China's unprecedented economic growth has come at the cost of having extensive air pollution. To tackle air pollution, environmental governance in China has undergone considerable reforms. The most salient change is that the central government ostensibly treats environmental quality on a par with economic growth, when evaluating the performance of local officials for promotion. Linking political promotion with environmental performance has been shown to improve air quality (Chen et al., 2018; He et al., 2020a; Wu and Cao, 2021); however, the effects are heterogeneous across regions. Economic growth remains the top priority in poor regions, in which air pollution continues to be tolerated by local officials and their supervisors in upper levels of government. Other considerations also have a role. The promotion of incumbent officials depends upon a range of metrics, such as age and education. For incumbent officials approaching retirement age, the prospects of being promoted are drastically reduced, together with their incentive to protect the environment. Corruption and vested interests also hinder effective governance, which complicates environmental performance in China.

2.2. Mechanisms linking economic growth, air pollution and political trust

We build a simple conceptual framework that demonstrates that economic growth builds political trust while air pollution, as a by-product of economic growth, can erode it. To facilitate our discussion, we consider political trust as a specific form of social capital (Coleman 1990; Putnam, 1993). While social capital is conductive to economic growth, the reverse relationship is not necessarily positive, as several studies have found that growth may undermine social capital (Routledge and von Amsberg, 2003).

We formulate political trust (S) as $S = f(Y, P)$, where Y denotes economic growth or per capita GDP, and P refers to air pollution which is the by-product of growth, $P=P(Y)$. Taking the first derivative we have:

$$\frac{\partial S}{\partial Y} = \frac{\partial f}{\partial Y} + \frac{\partial f}{\partial P}\frac{\partial P}{\partial Y} \tag{1}$$

The first term on the right-hand side is positive as economic growth provides resources for investment in social capital. However, economic growth in China has been accompanied by the intensive use of fossil fuels and, thus, high air pollution, making $\frac{\partial P}{\partial Y}$ positive. Higher living standards, due to economic growth, also increase citizens' environmental awareness. Government intervention is, hence, increasingly needed to mitigate environmental degradation. Less effective pollution controls generate citizen dissatisfaction towards the government, thus impairing political trust. That is, $\frac{\partial f}{\partial P}$ is negative. Pulling this together, the second term on the right-hand side is negative. The total or net effects of economic growth on political trust depend on the magnitude of the two terms, which may evolve over time and is ultimately an empirical question. Now we proceed to discuss how political trust is affected by air pollution.

2.2.1. Direct mechanisms

The most direct link between air pollution and political trust is for those living within the vicinity of polluting firms. These individuals are most exposed to severe air pollution and may be eager to shut the polluting firms down. At the same time, though, most local governments value the jobs and tax revenue generated by polluting firms and may be reluctant to make them close. If local government refuses to act, this could prompt citizens to protest, a collective action that broadly undermines political trust. In fact, pollution has been the number one cause of social unrest (Cunningham et al., 2020), accounting for over 50 per cent of mass protests in China (Annual Report on the Development of China's Rule of Law, 2014). If local government suppresses protesters in the name of maintaining social order, a vicious cycle of political distrust develops, in which trust in local government is further undermined.

Air pollution could impair political trust via lower life satisfaction and perceptions of government performance. Air pollution has brought inconveniences in daily life and even forced changes in people's lifestyle. Air pollution levels are checked more frequently than weather information in highly polluted regions (Patel, 2015). Children are kept home from school or restricted to classrooms during recess on high pollution days. People wear protective masks when outside and employ air purifiers when at home. These defensive behaviors lower life satisfaction, while local governments publicly claim the credit for sustaining high economic growth, which is the ultimate cause of environmental degradation. Hence, citizens exposed to prolonged air pollution may perceive local government as being responsible for their lower satisfaction with life due to air pollution and consequently, exhibit lower trust in it.

Moreover, Chinese citizens are increasingly aware that while the central government has been vocal in its wish to address air pollution, local governments are not always aligned with this aim, which further reduces political trust in local government.

Finally, people living in locations with higher levels of air pollution may be concerned about potential pollution data manipulation by local officials, who they may perceive as prioritizing their career over citizens' health and welfare. If local officials are manipulating pollution data to understate pollution levels, this exposes people to greater, but unknown, levels of health risk and drastically weakens the local government's credibility (Ghanem and Zhang, 2014; Greenstone et al., 2022). While understanding this mechanism requires sophisticated knowledge, media have widely exposed data manipulation and advised the public of the resulting potential health risks.[4] Rampant pollution data manipulation even prompted central government to establish a national monitoring network that directly administers air quality data (Greenstone et al., 2022).

[4] The widespread suspicion of air pollution manipulation dates from 2008 when the US Embassy in Beijing, and later US consulates in four large Chinese cities (Shanghai, Guangzhou, Chengdu, and Shenyang), began tweeting hourly $PM_{2.5}$ concentration readings. These readings were more detailed and typically higher than official Chinese statistics, which led to public doubts about the official readings and elevated concerns about air quality. There is considerable media coverage to this issue. For English articles, see e.g. https://www.wsj.com/articles/BL-CJB-15056; https://www.bbc.com/news/world-asia-china-15649829; https://chinadialogue.net/en/pollution/7828-china-promises-crackdown-on-fake-air-quality-data/For Chinese sources, see e.g. https://china.caixin.com/2017-11-25/101176037.html and http://www.rmzxb.com.cn/c/2015-04-02/475770.shtml.

2.2.2. Indirect mechanisms

We suggested earlier that political trust in China is largely dependent upon bureaucrats' performance in improving economic welfare. Two channels through which air pollution may indirectly affect political trust through changing economic welfare is via the effect of pollution on health and income. (Dong and Kübler, 2018).[5] $PM_{2.5}$ is extremely harmful to human health. Inhaling fine particulates triggers immune response and oxidative stress, leading to coughing, headaches and shortness of breath. Children, the elderly and those with pre-existing health conditions are particularly sensitive to $PM_{2.5}$, and prolonged exposure of it often leads to hospital admissions.[6] To avoid severe air pollution, outdoor activities are minimized, disrupting people's daily routines (Liu and Salvo, 2018). Deschenes et al. (2020) suggest that the decline in the rate of physical exercise in response to air pollution has increased the proportion of people overweight or obese, which poses another growing health risk in China.

Expenditure on health care, in response to pollution-induced health conditions, crowds out spending on other utility generating services, reducing welfare. Yang and Zhang (2018) show that a 1 per cent increase in $PM_{2.5}$ concentrations, increases medical expenditure by 2.9 per cent among urban households, corresponding to $US 2.5 billion additional medical expenditure for urban Chinese households as a whole. Relatedly, using universal debit and credit cards transaction records between 2013 and 2015 in China, Barwick et al. (2018) find that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ is associated with $US 4.6 billion out-of-pocket medical expenditure.

Moreover, poor health due to exposure to air pollution may impair labor productivity, and, hence, income, which further reduces political trust. Existing studies have found consistent evidence that air pollution impairs labor productivity in different settings (see e. g. Graff Zivin and Neidell, 2016; Chang et al., 2016; Chang et al., 2019; He et al., 2019). He et al. (2019) exploit daily variations in $PM_{2.5}$ concentrations in two highly-polluted manufacturing sites and find that a 10 $\mu g/m^3$ prolonged increase reduces daily industrial output by 1 per cent. Chang et al. (2019) study call centers, a cognitively demanding environment, and find that a 10-unit increase in the AQI reduces the number of daily calls answered by 0.25 percent.

3. Dataset and empirical strategy

3.1. Dataset

3.1.1. CFPS

We use four waves of the CFPS conducted in 2012, 2014, 2016 and 2018 to estimate the relationship between $PM_{2.5}$ and political trust in local government. The CFPS, which was launched in 2010 by the Institute of Social Science Surveys (ISSS) with Peking University, employs a multistage probability sampling procedure. It is nationally representative, covering 162 counties or districts (counties hereafter) across 25 mainland provinces that represent 95 per cent of the total population in China. During the first wave, the CFPS completed interviews with 33,600 individuals living in 14,798 households. These individuals were reinterviewed biennially. The CFPS provides information on interview date and county of residence for each respondent, enabling us to match them with county-level $PM_{2.5}$ concentrations.[7]

In the CFPS, political trust in local government has been consistently recorded since the 2012 wave.[8] Respondents were asked to rate their levels of political trust in local government on a scale from 0 to 10 where 0 indicates no trust at all and 10 extremely high trust.

Due to the political sensitivity of this question, self-reported political trust during a face-to-face interview could be biased because respondents may be reluctant to answer truthfully. We perform several checks to ensure that self-censorship, in which citizens feign positive attitudes towards the regime, is less likely to bias our estimates. The results of these checks are reported in Online Appendix B. First, we show that self-reported political trust has high internal validity, with political trust being low among individuals who had previously clashed with local government officials. Second, we find that self-reported political trust does not exhibit an abnormally compressed distribution around certain "politically correct" answers. Third, the overall distribution of self-reported political trust recorded in the CFPS is similar to that measured via the Asian Barometer Survey, which is an anonymous online survey.[9] Finally, we note that recent studies have shown that the Chinese government has become more tolerant of people expressing critical views of local government (see eg. Chen and Yang, 2019; Wang, 2013), which may encourage respondents to answer truthfully. In robustness checks, we construct a self-censorship index for each respondent and include it into our baseline specification. We find the estimated coefficients remain qualitatively the same to our baseline results. Nevertheless, it is important to acknowledge that we still cannot fully rule out bias due to self-censorship, as the true distribution of political trust among CFPS respondents is unknown.

[5] Other mechanisms include, but are not limited, to inequalities in exposure to air pollution and accessing the public medical system. We maintain that these mechanisms are strongly related to income and, thus, cannot be considered as principal mechanisms underlying the relationship between air pollution and trust in local government.

[6] Media reports suggest that, during haze days, hospitals in China are inundated with patients with recurrent respiratory symptoms; for example, see Waldmeir (2013) and Xu and Hou (2014).

[7] Importantly, the CFPS not only records the county in which respondents lived at the time of interview, but records where they lived previously, enabling us to control for endogenous migration.

[8] For this reason, we do not use the 2010 wave.

[9] These checks are in the spirit of Chen and Yang (2019).

Another problem, which is shared with other studies using self-reported trust measures, is that respondents may have different perceptions of political trust. For instance, Ratigan and Rabin (2020) find that marginalized individuals have different perceptions of political trust than their privileged counterparts. Therefore, we cannot be certain that one respondent's higher trust rating does not simply reflect his/her lower standard of trust. While we acknowledge that perceptions of political trust are intrinsic to respondents and that this problem cannot be completely overcome, we seek to address it in three ways. We first use more homogeneous subsamples, such as high-income or better-educated cohorts, among which understanding of political trust is arguably more similar. Second, we control for trust in strangers, which is typically used to benchmark one's generalized trust, in our baseline specification. Finally, we estimate the effect of air pollution on county-level political trust, which is averaged from respondents belonging to the same county. Reassuringly, our main finding remains intact.

We restrict our sample to individuals aged 18 years and above and to those who answered the question about political trust in local government. The response rates are similar between trust in local government (91.40 per cent) and trust in parents (91.41 per cent) and strangers (91.46 per cent) in which self-censorship is absent. We perform a paired-sample proportion difference test and cannot reject the null hypothesis that response rates to these questions about trust are equal. As such, non-responses are unlikely to be biasing our estimates. We exclude individuals for whom the interview date is not recorded and those who did not provide their usual residential address. Online Appendix C shows the distribution of interview dates for our sample. It spans all months, which help us to isolate the impact of air pollution from seasonality.[10] Due to strict migration controls associated with household registration, known as *hukou*, approximately 93 per cent of individuals living in rural counties in 2010 had been living in the same counties since their birth.[11] This feature ensures that migrant workers, whose exposure to air pollution is harder to pinpoint, are less likely to bias our estimates. In robustness checks, we exclude those who had moved, and those without a local *hukou*, and get qualitatively the same results.

3.1.2. Satellite derived $PM_{2.5}$ concentrations

We use $PM_{2.5}$ to proxy air pollution for three reasons. First, $PM_{2.5}$ is a primary ambient pollutant which is prevalent across China. In 2018, 190 out of 338 monitored cities failed to meet the annual standard of 35 μg/m^3 mandated by the Chinese government (Ministry of Ecology and Environment of the People's Republic of China, 2020), and none of them met the 10 μg/m^3 guidelines suggested by the WHO (WHO, 2018). Second, $PM_{2.5}$ can penetrate deep into lungs and carry toxins to other organs that have serious health implications. High levels of $PM_{2.5}$ irritate respiratory and cardiovascular systems, leading to aggravated asthma, lung disease and heart attacks (Barwick et al., 2018; He et al., 2020c).[12] Even a mild dose of $PM_{2.5}$ is known to reduce labor productivity, and trigger short-term anxiety and depression (Zhang et al. 2017, 2018; Chang et al., 2019). Finally, there is a growing awareness of the environmental effects of $PM_{2.5}$ in the Chinese media (Tu et al., 2020), which has encouraged more people to take defensive measures, such as wearing facemasks and using air purifiers, to avoid excessive exposure (Zhang and Mu, 2018; Ito and Zhang, 2020).

We obtain data on monthly $PM_{2.5}$ concentrations over the period 2010–2019 from van Donkelaar et al. (2019). This dataset is derived through fitting satellite AOD retrievals with a chemical transport model.[13] It is available at the $0.01^\circ \times 0.01^\circ$ resolution level for mainland China.[14] We merge the satellite derived $PM_{2.5}$ dataset with a map of Chinese counties and extract the spatially averaged monthly $PM_{2.5}$ concentrations for each county surveyed in CFPS.

For our purposes, the satellite derived $PM_{2.5}$ concentrations are more appropriate than the official $PM_{2.5}$ dataset from ground air quality monitoring stations. The primary reason is that the official $PM_{2.5}$ were not systemically collected until early 2014. Another reason is that ground monitoring stations are strategically placed in large and medium cities with dense populations (Fan et al., 2020). However, the CFPS covers a large number of rural counties that are not monitored. Thus, using the ground monitor data may introduce selection bias. A further concern is that official air quality data may have been manipulated by local government (Ghanem and Zhang, 2014). While the central government has mitigated this issue through directly administering air quality data, this practice is limited to automatic and real-time reporting stations that have only recently been deployed (Greenstone et al., 2022).

Fowlie et al. (2019) point out that satellite derived $PM_{2.5}$ concentrations is not a direct measure of air pollution and that the error structure is still poorly understood. Online Appendix D provides cross comparisons between satellite derived $PM_{2.5}$, official $PM_{2.5}$ from ground air quality monitoring stations (albeit with a shorter time span) and the $PM_{2.5}$ concentrations collected by the US Embassy and Consulates in China. All are highly correlated, which is reassuring. As a check on our results using satellite derived $PM_{2.5}$ concentrations we also use $PM_{2.5}$ concentrations from ground air quality monitoring stations, acknowledging that they are only available for a shorter time period and could be subject to manipulation and selection bias.

[10] Most interviews were conducted in summer or winter as those seasons largely overlap with the summer and winter breaks of the college students who were employed to interview respondents in CFPS.

[11] *Hukou* refers to the household registration system (HRS). The HRS limits where Chinese citizens may live, work and obtain public health care or schooling. Citizens can physically move to other places with better ambient air quality. However, without registering their local *hukou*, migrants are excluded by local government from assessing those social benefits.

[12] For example, He et al. (2020c) find that a 10 μg/m^3 spike in $PM_{2.5}$ is associated with 3.25 per cent more deaths due to cardiorespiratory diseases. Fan et al. (2020) report that a 10-point increase in the weekly Air Quality Index, which is mainly driven by variations of $PM_{2.5}$ and PM_{10}, is responsible for a 2.2 per cent increase in overall mortality.

[13] AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution.

[14] The AOD retrievals are obtained from multiple satellites including NASA Moderate Resolution Imaging Spectroradiometer (MODIS), the Multi-angle Imaging Spectroradiometer (MISR) and SeaWIFS. The detailed construction process is discussed in van Donkelaar et al. (2019). We thank Professor Aron van Donkelaar for sharing the restricted and monthly-frequency $PM_{2.5}$ concentrations with us.

Fig. 1 maps the mean $PM_{2.5}$ concentrations for areas surveyed by CFPS over the period 2010–2019. Because we are not allowed to disclose the precise locations of counties surveyed by CFPS, we only highlight the provinces to which counties surveyed in CFPS are affiliated.[15] Darker colors refer to higher $PM_{2.5}$ concentrations. $PM_{2.5}$ levels are alarmingly high in Beijing, Hebei and Henan, with mean concentrations between 58 and 84 μg/m^3, but are much lower in Southwest China. In Figure A1, we map changes in $PM_{2.5}$ concentrations over the same period, to assess the trend in air quality. The most salient $PM_{2.5}$ reductions occur in those regions that have traditionally been highly polluted. These substantial spatial and temporal variations allow us to estimate the causal effect of air pollution on trust in local government.

3.1.3. Thermal inversion

We construct a measure of thermal inversions from using NASA's MERRA reanalysis dataset. It reports six-hourly air temperature at the $0.5^\circ \times 0.625^\circ$ resolution grid for each of the 72 atmospheric layers, ranging from the surface to 39,356 m in altitude.[16] For our main results, we extract the air temperature at the 72nd layer (representing approximately 110 m in altitude) and the 70th layer (representing approximately 550 m in altitude) and then match them with the location of the counties surveyed in the CFPS. The use of layers to capture thermal inversions follows the approach in related studies (Chen et al., 2022; Deschenes et al., 2020).[17] We code a thermal inversion as occurring if the air temperature at the 70th layer is higher than that of the 72nd layer in a county. We aggregate the occurrences of thermal inversion across all 6-h periods in the selected exposure window preceding the interview month. Note that our second layer is higher than that employed by both Chen et al. (2022) and Deschenes et al. (2020), as we want to capture more stable thermal inversions.

Figure A2 plots the average number of thermal inversions for each month between 2010 and 2019. A large share of inversions occur in winter, in which long nights and calm winds allow for ground temperature to cool faster than air temperature. In robustness checks, we also employ air temperature using different layers and alternative measures based on thermal inversion strengths and find that our main results remain qualitatively similar.

3.1.4. Other weather controls

We control for a set of weather variables – temperature, air pressure, cumulative precipitation, relative humidity, sunshine duration, wind speed and wind direction of the maximum wind speed – that are potentially correlated with air pollution. Daily weather information between 2010 and 2019 are obtained from 820 synoptic weather stations operated by the China Meteorological Administration. Our weather dataset contains the exact coordinates of each weather station, enabling us to match the daily weather information with each of the counties that were surveyed in the CFPS. Specifically, we use the inverse distance weighting method, employing 100 km as the cutoff distance. Using 150 km and 200 km distance cutoffs produce almost the same results.

Table A1 presents summary statistics of the key variables. The mean score of trust in local government across the four waves from 2012 to 2018 is 5 out of 10. Respondents expressed higher trust in local government than they did trust in either Americans or strangers, but less trust than in the neighborhood or respected professionals, such as doctors. There is heterogeneity in political trust across respondents. Table A2 reveals that political trust is lower among urban, educated, richer and unhealthy cohorts; who are arguably more averse to air pollution. Most respondents expressed some concern about environmental quality, with the mean score for environmental concern being 6.4 out of 10.

Air pollution and thermal inversion data are at the county-month level. In our sample, the monthly mean $PM_{2.5}$ concentrations is 45.26 μg/m^3, which is higher than the WHO (2018) recommended maximum of 10 μg/m^3 and China's "interim" standard of 35 μg/m^3. The average number of cumulative thermal inversions is 31.14 per month with a maximum of 120 per month. Thermal inversions are measured at the frequency of 6 h (maximum four times per day), so 120 refers to the extreme case that thermal inversion was detected almost all the time. There are also extreme cases in which no thermal inversion is detected in a county-month cell.

3.2. Empirical strategy

Our objective is to examine the causal effect of $PM_{2.5}$ concentrations on political trust in local government. To realize this aim, we estimate the following 2SLS model:

$$PM25_{cny} = \alpha_0 + \alpha_1 TI_{cny} + f\left(W_{cny}\right) + \lambda_{cy} + \omega_{cny} \tag{2}$$

$$Trust_{icmy} = \beta_0 + \beta_1 \widehat{PM25}_{cny} + f\left(W_{cny}\right) + \gamma_i + \lambda_{cy} + \varepsilon_{icmy} \tag{3}$$

In the second stage, $Trust_{icmy}$ denotes the level of political trust in local government revealed by individual i who resided in county c and was interviewed in month m of year y. $PM25_{cny}$ refers to the satellite derived, county-level, mean $PM_{2.5}$ concentrations during the

[15] This is under the terms of the agreement for using county-level restricted data - see http://www.isss.pku.edu.cn/cfps/en/data/restricted/index.htm?CSRFT=GHPL-KBBM-EPWZ-4V88-8R24-E6YI-LT9L-ONR2 for more information.

[16] The dataset and description of the dataset is available at https://disc.gsfc.nasa.gov/datasets/M2I6NVANA_5.12.4/summary?keywords=air%20temperature.

[17] The difference between the two selected layers refers to surface inversions that are an important predictor of ground air quality. According to Abdul-Wahab et al. (2005), using 110 m and 550 m layers (with the depth around 400 m) is likely to capture most surface thermal inversions. The other type is aloft inversions that occur far above the ground, and, hence, are less relevant to air quality.

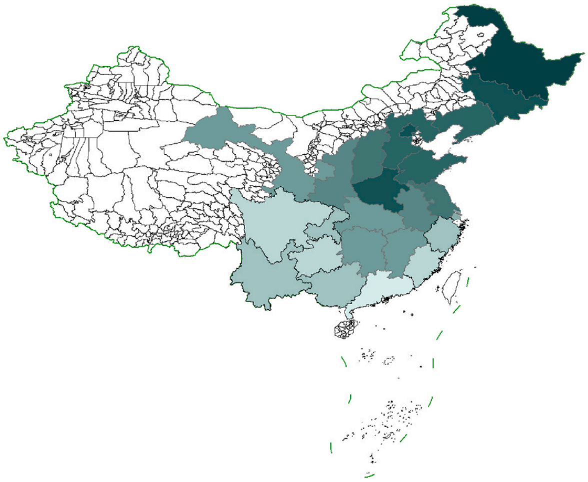


Fig. 1. Areas surveyed by CFPS and mean PM2.5 concentrations over the period 2010–2019. Note: Darker colors refer to higher $PM_{2.5}$ concentrations. Because we are not allowed to disclose the precise locations of counties surveyed by CFPS under the terms of the license agreement, we only highlight the provinces to which counties surveyed in CFPS are affiliated. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

exposure window n preceding the CFPS interview month m.

Since the OLS estimate of β_1 could be biased by measurement error and omitted variables, we use cumulative occurrences of thermal inversions over exposure window n, denoted by TI_{cny}, from the first-stage regression to instrument for $PM_{2.5}$ concentrations over the same window. The coefficient on α_1 is expected to be positive as more frequent thermal inversions trap air pollutants at the surface, leading to higher $PM_{2.5}$ concentrations. Thermal inversions are common meteorological phenomenon and, as such, their formation is independent of potential determinants of political trust. In Online Appendix E, we examine the association between the number of annual thermal inversions and major determinants of political trust, such as income and a set of welfare indicators. All are statistically insignificant and most are close to zero in magnitude. These results suggest that thermal inversions are unlikely to undermine political trust through indirectly affecting local economic variables.

To satisfy the exclusion restriction, and to ensure that thermal inversions only affect political trust through air pollution, we use flexible functions, $f(W_{cny})$, to control for weather variables. For temperature, daily mean temperatures over the exposure window are grouped into ten 6 °C wide bins, ranging from below −12 °C to above 32 °C. We omit temperature bin [10 °C 16 °C) to avoid multicollinearity. For air pressure, relative humidity, sunshine duration, cumulative precipitation, wind speed and the direction of the maximum wind speed, third-order polynomials are used to transform their mean values. We include individual fixed effects γ_i to control for any time-invariant individual characteristics and county-by-year fixed effects λ_{cy}, in order to captures annual shock that are specific to each county. We include a provincial-specific time trend, which captures the secular change in political attitudes at the province level.

We follow Deschenes et al. (2020) in using two-way clustering at the individual and county-year-month levels. It controls for persistence in political trust for the same individual across different waves of the CFPS survey and potential autocorrelation within each county-year-month cell. Our results are also robust to a set of different clustering methods.

Overall, our identification relies on comparing political trust of the same individual in a more inversion intensive and, thus, more polluted period versus a less inversion intensive and less polluted period, after we adjust for county-by-year fixed effects and weather shocks.

There is no consensus in the existing literature as to the length of the exposure window, n. Intuitively, the length of exposure window should allow enough time for the pathways through which air pollution influences trust in government to have effect. A short exposure window, for example, might fail to capture the health effects that are attributed to accumulated exposure of air pollution. On the other hand, people might become habituated to persistently higher air pollution over time, making a very long exposure window inappropriate. To determine the appropriate exposure window, in terms of total months preceding the CFPS interviews, we follow a standard approach in the epidemiological literature (Velentgas et al., 2013). We first estimate a distributed lag model in which political trust is explained by lagged $PM_{2.5}$ concentrations, together with controls and fixed effects as described above. To stabilize estimation, several constraints, such as penalized splines and Gaussian processes, are imposed. We then calculate various information criteria for each model estimated. This two-step procedure is repeated for different lag structures, with the maximum lag capped at the 20th month preceding the interview.[18] We select the exposure window, based on the optimal lag structure for which the information criteria are minimized.

[18] Since we have no information on the exact day of interview, we exclude the month of interview to alleviate measurement error. We cannot extend the lag length beyond 20 months because the gap between two consecutive interviews are 20 months on average.

4. Empirical results

4.1. Baseline regression results

Table A3 contains results for the information criteria used to select the length of exposure window, *n*, to air pollution, which are obtained after estimating both OLS and 2SLS specifications. Most information criteria suggest that the optimal lag structure extends to either the 10th or 11th month before the interview month. To be conservative, we set the optimal exposure window equal to 11 months preceding the CFPS interview in our baseline analysis. In robustness checks, we consider exposure windows, from one to 20 months before the interview. The results are qualitatively similar when we employ the 10th month prior to the interview.

Table 1 presents the point estimates for $PM_{2.5}$ concentrations. We first present OLS estimates without correcting for endogenous exposure to air pollution. In column (1), we include individual and county-by-year fixed effects. In column (2), we also control for a provincial-specific time trend, which captures the secular change in political attitudes. The OLS results suggest that there is a small, unstable, and insignificant association between $PM_{2.5}$ concentrations spanning the past 11 months and trust in local government.[19]

OLS estimates are biased in the presence of omitted variables and measurement error. Therefore, we use cumulative occurrences of thermal inversions to instrument for $PM_{2.5}$ concentrations in the same exposure window. Before presenting the 2SLS results, we estimate the reduced-form regression of political trust on the number of thermal inversions. Since the reduced-form estimate is, in theory, proportional to the causal effect of interest (Angrist and Krueger, 2001), it can be seen as a validity check on our instrument. Columns (3) and (4) of Table 1 report the reduced-form results with, and without, the provincial-specific time trend. Both specifications suggest a negative and highly significant effect on trust in local government. Specifically, one additional thermal inversion decreases political trust by 0.0024–0.0031 units.

Columns (5) to (7) of Table 1 report the 2SLS estimates. We begin with a specification without weather controls. Column (6) adds weather controls and Column (7) further adds the provincial-specific trend. The first-stage results in the upper panel consistently show that the instrument is a powerful predictor of $PM_{2.5}$ concentrations. One additional thermal inversion in the past 11 months increases the mean $PM_{2.5}$ concentrations by 0.0301–0.0358 μg/m^3 over the same period. These estimates are close to Fu et al. (2021), who employ thermal inversions to identify the causal effect of $PM_{2.5}$ on firm productivity in China. To demonstrate that the instrument is not weak, we perform the Kleibergen-Paap Wald *rk F* test (Kleibergen and Paap, 2006). The *F*-statistics are much larger than the Stock and Yogo (2005) critical value of 16.38, implying that thermal inversion is a strong instrument for $PM_{2.5}$ concentrations.

The lower panel of columns (5) to (7) report the second-stage results. A one μg/m^3 increase in mean $PM_{2.5}$ concentrations over the past 11 months reduces respondents' political trust in local government by 0.0792–0.1107 units. Our preferred specification, column (7), shows that a one μg/m^3 increase in $PM_{2.5}$ concentrations reduces political trust by 0.106 units, equivalent to 4.1 per cent of one standard deviation. The 2SLS estimates are much larger than the OLS estimates in magnitude. This finding is consistent with the previous literature using thermal inversions to identify the exogeneous effects of air pollution on a range of socioeconomic outcomes (Arceo et al., 2016; Sager, 2019; Fu et al., 2021). We attribute the downward biased OLS estimates to measurement error in which the satellite-derived, county-level $PM_{2.5}$ concentrations are used to proxy individual-level exposure.

To put our estimates into context, consider a nationwide exogenous decrease in $PM_{2.5}$ concentrations by 10 μg/m^3. This reduction would be equivalent to lowering the annual mean $PM_{2.5}$ concentrations from the current mean level to 35 μg/m^3, which is China's interim standard. Such a reduction would boost trust in local government by 1.064 units, equivalent to 21.2 per cent evaluated at the mean.

4.2. Heterogeneity analysis results

We now explore the heterogeneous effects across different cohorts to further characterize the $PM_{2.5}$ impacts. The use of cohorts with similar socioeconomic status can mitigate potential bias resulting from respondents having different perceptions of political trust. The results are summarized in Table 2. We first separate the 162 counties surveyed in CFPS into high- and low-pollution subsamples using their mean $PM_{2.5}$ concentrations over the period 2010–2019. Columns (1) and (2) of Table 2 show that the association between $PM_{2.5}$ concentrations and political trust is slightly stronger in the high pollution subsample. The moderately different effects provide suggestive evidence that citizens acclimatize to high levels of air pollution.

In columns (3) and (4), we divide counties surveyed in CFPS according to whether air pollution deteriorated or improved over the sample period.[20] Although less than one third of counties experienced worse air pollution, the effect of $PM_{2.5}$ is much larger and highly significant. A one μg/m^3 increase in $PM_{2.5}$ concentrations reduces political trust by 0.233 units, equivalent to 8.9 per cent of one standard deviation. By contrast, the estimated effect is 0.090 or 3.4 per cent of one standard deviation among those who experienced $PM_{2.5}$ reductions.

We next assess heterogeneity by residential location. Columns (5) and (6) of Table 2 suggest that the coefficient is −0.503 among urban residents, which is almost five times our baseline estimate (−0.106). Note that this estimated coefficient should be interpreted

[19] We also perform OLS regressions with different exposure windows from the one month to 20 months. The coefficient on air pollution is mostly small and insignificant. Full results are available upon request.

[20] Over the period of 2010–2019, most counties surveyed in CFPS did not exhibit a secular increase or decrease in $PM_{2.5}$ concentration. To capture the changes in $PM_{2.5}$ concentration, we use the difference between the mean concentration in $PM_{2.5}$ from 2010 to 2012 and the mean concentration from 2017 to 2019.

Table 1
Baseline results.

	OLS		Reduced form		2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					First stage		
			Trust in local government		$PM_{2.5}$		
Cumulative Thermal Inversions			−0.0031***	−0.0024***	0.0358***	0.0301***	0.0308***
			(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
KP rk *F*-statistic					195.9	228.4	237.8
					Second stage		
Dependent variable	Trust in local government				Trust in local government		
$PM_{2.5}$	−0.0044	0.0011			−0.0792***	−0.1107***	−0.1064***
	(0.009)	(0.009)			(0.0226)	(0.029)	(0.028)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	No	Yes	Yes
Provincial specific time trend	No	Yes	No	Yes	No	No	Yes
No. of individuals	33,219	33,219	33,219	33,219	33,219	33,219	33,219
No. of Obs.	106,033	106,033	106,033	106,033	106,033	106,033	106,033

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls consist of ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP rk *F*-statistic is the Kleibergen-Paap Wald rk *F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

with caution as the F-statistic is 9.875, which is slightly less than the widely accepted threshold value 10 for a strong instrument. There are more complex sources of air pollution in urban areas, such as traffic and public heating, which weaken the predictive power of thermal inversions. Another potential explanation is that the relationship between $PM_{2.5}$ concentrations and thermal inversions is nonlinear, which might be weaker in more polluted urban areas. The effect for rural residents is insignificant and much smaller in magnitude. The different effects are unlikely due to lower air pollution in rural areas, as agricultural activities, such as straw burning, has been identified as one major source of particulate matters in China (Graff Zivin et al., 2020; He et al., 2020c). A plausible explanation for the result, however, is lack of awareness of air pollution in rural areas. This explanation coincides with the fact that many people in urban China have identified air pollution as a major trigger to recurrent respiratory symptoms, such as coughing and having a sore throat. Meanwhile, both He et al. (2020c) and Fan et al. (2020) note that few rural residents take measures to address air pollution and, hence, suffer greater adverse health effects. There is also possibility that rural residents suffer transboundary pollution from other counties; and they understand that it is beyond local government's capacity to control it. We address transboundary pollution in our robustness checks.

In terms of education attainment, results in columns (7) and (8) indicate that those with high school or above qualifications are more responsive to $PM_{2.5}$ exposure. A likely explanation is that educated cohorts tend to be more aware of the adverse health effects of air pollution.

Finally, we assess heterogeneity by income levels. On the one hand, high income individuals may possess more resources to offset the adverse effects of air pollution. Yet, on the other, higher income Chinese have demonstrated more postmaterialist values and increasingly criticized government for failing to protect air quality (Wang, 2013; Ahlers and Shen, 2018). In columns (9) and (10), we divide our sample into high- and low-income respondents, which are defined relative to their local average income levels.[21] These relative measures are only weakly associated with air pollution and, therefore, are less likely to suffer from endogeneity concerns. We find that a one μg/m^3 increase in $PM_{2.5}$ concentrations reduces political trust among relatively richer individuals by 0.2330 units, which is equivalent to 8.9 per cent of one standard deviation. By contrast, the estimated coefficient is only half of that for low-income cohorts, implying that material improvement remains the top priority for them.

4.3. Robustness checks

4.3.1. Alternative exposure windows

As a first robustness check, we vary the exposure window over which $PM_{2.5}$ affects respondents' trust in local government. Fig. 2 summarizes the 2SLS estimates over different exposure windows using two specifications. Panel A controls for individual and county-by-year fixed effects, while panel B further incorporates a provincial-specific time trend. Each dot refers to a point estimate corresponding to a specific exposure window. The instrument used is the cumulative occurrences of thermal inversion in the same exposure

[21] In CFPS, to elicit income status respondents are asked the following question: "What is your income level relative to others in your local area?" There are five options from one to five, where one refers to "very low" and "very high". To sharpen our comparison, we exclude respondents who report "same as the local average".

Table 2
Heterogeneity.

	High $PM_{2.5}$	Low $PM_{2.5}$	Deteriorated	Improved	Urban Residence	Rural Residence	Educated	Less Educated	High Income	Low Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Second Stage										
$PM_{2.5}$	−0.1636***	−0.1346**	−0.2334***	−0.0899***	−0.5025**	−0.0822	−0.191**	−0.0857***	−0.2330***	−0.1063**
	(0.061)	(0.061)	(0.110)	(0.033)	(0.244)	(0.146)	(0.075)	(0.029)	(0.061)	(0.055)
First Stage										
Cumulative Thermal Inversions	0.0213***	0.0218***	0.0156***	0.0331***	0.0071***	0.0109***	0.0196***	0.0362***	0.0222***	0.0276***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
KP *rk F*-statistic	56.44	60.89	24.08	104.4	9.875	21.18	59.99	259.7	72.71	150.4
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	51,398	54,549	31,745	74,146	47,620	54,295	22,367	77,734	44,305	33,891

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The number of observations differ according to the sample considered. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is the total number of thermal inversion occurrences in the same period. "High $PM_{2.5}$" and "Low $PM_{2.5}$" are defined for counties' local long-term $PM_{2.5}$ concentrations. Above the median value are denoted as High $PM_{2.5}$ counties. "Deteriorated" and "Improved" refer to whether respondents live in counties which experienced negative and positive changes in $PM_{2.5}$ concentrations, respectively. "Urban Residence" and "Rural Residence" refers to subsamples whose usual residential address is in urban and rural areas, respectively. "Educated" refers to individuals with high-school or above qualifications. Weather controls consist of ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

window. We also construct 95% confidence intervals and denote them with whiskers.

The negative and significant effect of $PM_{2.5}$ concentrations on political trust is robust to exposure windows lasting for eight to 11 months preceding the interview. Our baseline result, which is based on the optimal 11-months long exposure window, exerts the largest effect. The insignificant results for one to seven months imply that trust in local government responds to prolonged, rather than temporal, elevation of air pollution.[22] The results are also insignificant for exposure windows of 12 months or longer. One plausible explanation for this result is that respondents psychologically adapt over time to elevated air pollution, through various coping strategies such as wearing facemasks, using air purifiers or simply staying indoors (Liu and Salvo, 2018; Zhang and Mu, 2018; Tu et al., 2020). This explanation is supported by a recent survey by Cunningham et al. (2020), which finds that Chinese residents become habituated to local air pollution over time and once habituated only exhibit responses when air quality deviates significantly from typical levels.

The dynamic relationship between air pollution and political trust is implied by our conceptual framework. The net political gain from higher economic growth is positive but becomes negative once air pollution reaches a critical level. This dynamic relationship also resembles the pattern found in Deschene et al. (2020) for the effects of $PM_{2.5}$ on body weight. They, however, found that exposure windows were significant for 11–13 months, which is slightly longer than us.

Note that few of our estimated coefficients are positive, though insignificant, after extending to exposure windows of 13 months and longer. Air pollution has a salient seasonal pattern in China, which is typically severe in winter and mild in summer. Extending the exposure window to 13 months means that the first stage thermal inversion – $PM_{2.5}$ concentration relationship enters another 12-months cycle, in which variation used to identify the relationship is limited. We do find that the first-stage results become weaker with exposure windows longer than 12 months. In unreported results, we controlled for seasonal fixed effects and still a found positive, but insignificant, effect of $PM_{2.5}$ concentrations, possibly reflecting that most interviews were conducted in the summer.

To ensure that our main results are not driven by $PM_{2.5}$ concentrations in the 11th month prior to the interview we estimate its individual effect. In column (2) of Table A4, we show the single month's effect is significant but much smaller in magnitude, being less than one tenth of our baseline estimate. In column (3), we regress political trust on both periods' $PM_{2.5}$ concentrations in the same specification to create a horse race. The 11th month's $PM_{2.5}$ concentrations loses significance, while the mean $PM_{2.5}$ concentrations in the past 11 months is highly significant and the coefficient is comparable to our baseline estimate. We replicate the same analysis for individual months from the 7th to the 12th month preceding the interview and obtain the same conclusion.[23] These results reinforce the conclusion that political trust is responsive to prolonged, rather than temporal, elevation of air pollution.

4.3.2. Excluding categories of respondents and provinces

Table A5 examines whether, and to what extent, the baseline estimate is sensitive to excluding certain respondents. Column 1 reproduces our preferred specification from Table 1 to facilitate comparison. In column (2), we exclude respondents who have had previous conflict with local officials. The result is similar to our baseline estimate in terms of magnitude and significance. In column (3), we further exclude respondents who reported having had negative encounters with government officials. The coefficient is slightly reduced, but remains highly significant. The weaker association implies that such respondents, who are likely to have lower political trust to begin with, are more likely to blame air pollution on local government.

In column (4), we exclude respondents with family background labelled as "landlord", "capitalist", or "reactionary farmers" during the 1945–1950 Communist Revolution. Those families suffered persecution during the Cultural Revolution (1966–1976), and their descendants have been shown to exhibit higher levels of distrust in government (Chen and Yang, 2019). We find a small change in the estimated coefficient after removing them.

In Column (5), we exclude members of China's Communist Party (CCP) who are disproportionally exposed to party propaganda and may have higher trust in government. Table A2 suggests that political trust among CCP members is 5.430, significantly higher than 4.964 for other respondents. While CCP members account for less than one tenth of total observations, excluding them moderately increases the magnitude of the estimated coefficient to −0.136, implying that CCP members' trust in local government is more resilient to air pollution.

In Column (6), we exclude those are more likely to be exposed to household air pollution (HAP). HAP exerts similar health impacts to $PM_{2.5}$ and, therefore, may confound the estimated effect of ambient air pollution on political trust (Kurata et al., 2020). Since the level of HAP exposure is unknown, we proxy for it using major cooking fuels, among which straw and firewood are leading sources of HAP. The effect of $PM_{2.5}$ doubles to −0.226. However, we should be cautious in interpreting this result, given that this subsample contains many urban residents, who are arguably more averse to air pollution.

One might be concerned that our results are biased by transboundary pollution. Transboundary air pollution may affect trust in

[22] For exposure windows of one and two months preceding the interview month, $PM_{2.5}$ concentrations have a positive and marginally significant effect on political trust in local government. One potential explanation is that the benefits from higher economic growth outweigh the cost from induced air pollution over a short period, resulting in a net gain in political trust. More economic activities could result in an immediate increase in the economic welfare of households (e.g. more working opportunities and higher income), which increase their satisfaction, and possibly, trust in local authorities. By contrast, air pollution, as a by-product of economic activities, would not trigger public discontent, until it reaches levels that become intolerable. We don't want to place too much emphasis on the results for exposure windows of one and two months preceding the interview month, though, given that the positive effect of $PM_{2.5}$ concentrations in the previous two months is not robust to alternative sets of fixed effects and different clustering strategies. Detailed results are available upon request.

[23] Full results are available upon request.

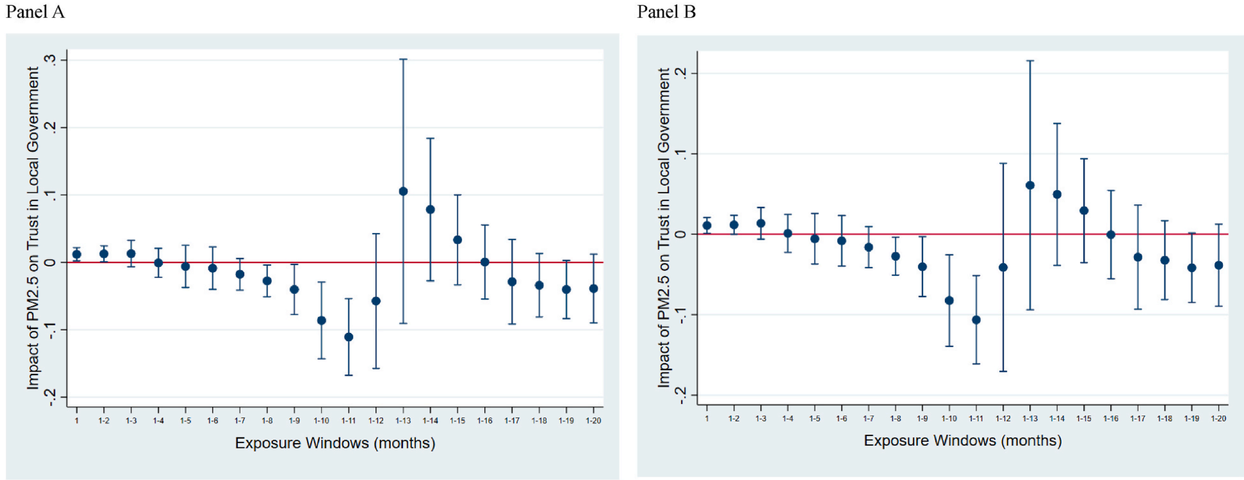


Fig. 2. Effects of $PM_{2.5}$ concentrations with different exposure windows on political trust in local government. Note: Panel A controls for individual and county-by-year fixed effects, while panel B further incorporates a provincial-specific time trend. Each dot refers to the 2SLS point estimate corresponding to a specific exposure window. The instrument used in these estimations is the cumulative occurrences of thermal inversion over the same window. The whiskers denote 95% confidence intervals.

local government differently, depending on whether local citizens can distinguish the sources of air pollution. There are three scenarios. First, local citizens have limited knowledge to distinguish between the sources of air pollution and, therefore, the established baseline result should be robust to excluding counties that are prone to transboundary air pollution. Second, local citizens know that air pollution is generated externally and blame government for failing to protect them. In this scenario, air pollution may have a stronger negative effect on political trust. Third, local citizens know that they are exposed to transboundary air pollution, but also understand that it is beyond local government's ability to address it. In this final scenario, we would expect air pollution to exert a weaker effect on political trust. In the final column of Table A5 we address the potential confounding influence of transboundary air pollution. To do so, we exclude respondents that are disproportionally exposed to transboundary $PM_{2.5}$. Following Wu and Cao (2021), we treat a county, and its residents, as being prone to transboundary $PM_{2.5}$ when there is at least one major coal-fired power plant ($\geq$ 1 million kW) located upwind, and within 100 km, of the county.[24] Imposing this condition excludes 13 counties and we find that locally generated $PM_{2.5}$ exerts a similar effect to our baseline result. While this result is in line with the explanation that local residents have limited knowledge regarding air pollution sources, it should be taken as suggestive, as we only consider transboundary $PM_{2.5}$ from power plants.

We also examine the sensitivity of our baseline estimate to excluding provinces on a case-by-case basis to see if respondents in any province are driving the results.[25] The 2SLS estimates, along with the 95% confidence intervals, are summarized in Figure A3. All estimates are negative and highly significant and most are close to the magnitude of the baseline estimate.

4.3.3. *Effect of air pollution on trust in other groups and controlling for generalized trust*

Column (1) of Table A6 is our baseline estimate. In column (2), we control for trust in strangers, which is often used as a proxy for respondents' general trust (Nunn and Wantchekon, 2011), to address the concern that political trust is self-reported and may depend upon one's general trust. Controlling for general trust also helps mitigate potential bias from respondents having different perceptions of political trust. We find a small change in our baseline estimate, while respondents' general trust is positively and significantly correlated to one's political trust, in line with expectations. In column (3), we control for trust in neighbors, instead of strangers, and our main results remain robust. These results also suggest that air pollution directly undermines citizens' trust in government, rather than through lowering their general trust.

As another way to mitigate different perceptions in political trust across respondents, we use county-level political trust, which is the mean value from all respondents within the same county. Our county-level regression includes county fixed effects which capture time invariant components of political trust related to culture or history and year effects that are used to control for national-level shocks to political trust. In line with our individual-level analysis, we also control for the province-specific time trend. In Online Appendix F, we find that $PM_{2.5}$ concentrations continue to exert a negative, albeit less significant, effect on county-level political trust. The significant effect is detected for exposure windows spanning 10 and 11 months, which is largely consistent with our baseline

[24] Ideally, we should include all other major polluting sources, such as steel smelting firms. While the Annual Survey of China's Industrial Firms contains relevant information, the detailed location, measured in longitude and latitude, is missing for at least half of the industrial firms.

[25] Municipalities including Beijing, Tianjin, Shanghai, Chongqing have provincial status in China. As such, we also call them "provinces" for simplicity.

finding.[26] Note that the first-stage results, together with the KP *rk* F test, are much weaker, particularly for exposure windows longer than 12 months. This makes sense, given that our county-level dataset contains only 635 observations and that there are a large set of fixed effects and weather controls.

In columns (4) to (6) of Table A6, we replace political trust with trust in parents, physicians, and Americans as the dependent variable. There is no theoretical relationship between air pollution and trust in these groups and any significant effect of $PM_{2.5}$ on trust in these groups would suggest that our results could be due to confounding factors. In each of columns (4) to (6), we find small and insignificant results, which reinforces the robustness of our findings.[27]

4.3.4. Checks on the validity of our instrument

Table A7 examines the sensitivity of our baseline estimates to alternative identification strategies. In column (2), we follow Deryugina et al. (2019) and use the limited information maximum likelihood (LIML) estimator. We find a small change in the baseline estimate.

Next, to demonstrate the relevance of our instrument, we follow Fu et al. (2021) and randomly reassign the $PM_{2.5}$ concentrations to the inversion and weather data. We repeat this procedure and re-estimate the model one hundred times to increase the power of the test. Figure A4 summarizes the estimates along with their 95% confidence intervals. Only seven of the one hundred estimates are marginally significantly different from zero.

In the main results, our instrument – the cumulative occurrence of thermal inversions – is defined for temperature differences between the 72nd layer (110 m) and the 70th layer (550 m). In column (3) of Table A7, we replace the 70th layer with the lower 71st layer, approximately 340 m in altitude following Deschenes et al. (2020). We find a slightly larger estimate.

One of the main reasons for using an instrument is to address measurement error in individual-level exposure to air pollution. However, air temperatures, which are used to construct thermal inversions and are also satellite-based products, may also be subject to measurement error. Unfortunately, air temperatures are point estimates, without standard deviations, which prevents us from constructing thermal inversion using a stricter threshold.[28] Thus, we employ air temperature at the higher 69th layer (approximately 640 m in altitude) and calculate the difference in temperature between that and the 72nd layer (110 m). The larger distance gap between the two layers makes the constructed thermal inversions less prone to temperature measurement error. In column (4), we find a smaller, but still highly significant estimate.[29]

In column (5), we use the strength of thermal inversions to instrument for $PM_{2.5}$ concentrations. It is defined using the 110 m layer temperature minus the 550 m layer temperature.[30] A positive difference indicates the nonexistence of thermal inversion and is truncated to zero. A negative difference indicates the existence of a thermal inversion, and its magnitude captures the inversion strength. We aggregate the inversion strength, which is measured at six-hourly frequency, into the specified exposure window, over the 11 months preceding the interview. One advantage of using the strength measure is that it has greater predictive power in counties where thermal inversions are very frequent. The first-stage results uncover that the thermal inversion strength is an equally powerful instrument for air pollution, and the estimated coefficient of instrumented $PM_{2.5}$ changes little.

In column (6), we use the official $PM_{2.5}$ data from ground air quality monitoring stations. This check is also motivated by the fact that both $PM_{2.5}$ concentrations and thermal inversions are constructed from using NASA's satellite products and that there could be mechanical linkages between them, driven by satellite attributes. Because most rural counties are not deployed with monitoring stations, we spatially interpolate the $PM_{2.5}$ concentrations using inverse distance weighting.[31] The estimated coefficient is remarkably close to our baseline estimate.

In column (7), we use AQI, a composite measure of air pollution consisting of PM_{10}, SO_2, NO_2, CO and O_3, which is available from April 2014 onward. We find that a one unit increase in AQI reduces trust in local government by 0.0499 units, which is smaller than our baseline effect as well as that documented in Alkon and Wang (2018). The larger effect of $PM_{2.5}$ is consistent with its bigger health impact and more widespread media attention (Tu et al., 2020).

Our identification strategy relies on thermal inversion induced exogenous variations in $PM_{2.5}$ concentrations. However, as shown in Table A1, there are counties in which thermal inversions are not detected at the month-county level. While all counties have experienced positive thermal inversions over the exposure window, identification would be weaker in low frequency thermal inversion regions compared to that in high frequency counties. In column (8), we exclude counties that are in the bottom 5 per cent of monthly thermal inversions and find a moderately stronger effect of $PM_{2.5}$ concentrations. In Online Appendix G, we also exclude counties that are in the bottom 10 per cent of monthly thermal inversions and find qualitatively the same result to our baseline estimate. There could be systemic differences between counties with high- and low-frequency thermal inversions. We divide our sample according to median frequency of thermal inversions. We find both estimated coefficients of $PM_{2.5}$ are highly significant and similar in magnitude. Note,

[26] We use the month with which the most interviews were conducted to proxy the county's "average" interview month.

[27] We also use alternative exposure windows from one to 20 months and document consistently insignificant results. Full results are available upon request.

[28] The stricter rule for detecting thermal inversions is $Tem\_lower\ layer + Std.Dev < Tem\_upper\ layer$. The latest description document for air temperature products can be found at https://gmao.gsfc.nasa.gov/pubs/docs/Bosilovich785.pdf.

[29] Using even higher layers, at either 68th or 67th layers, leaves our estimate qualitatively the same. Full results are available upon request.

[30] We also define thermal inversion strength using alternative layers and obtain very similar results. Full results are available upon request.

[31] We set the cut-off distance at 150 km. Using the ordinary Kriging approach or an alternative cut-off distance at 100 km does not change our results meaningfully. Full results are available upon request.

that the first-stage results, in terms of both the KP *rk* F-statistic and the estimated coefficient of thermal inversions, are larger for counties with relatively high frequency of thermal inversions. These results provide further support to our identification strategy.

Another threat to our identification strategy is that thermal inversions may influence political trust through channels other than air pollution. Governments could issue air pollution warnings based on thermal inversions and order the temporary shutdowns of heavy polluting firms. This could influence political trust by sending the message that public health is being prioritized higher than economic growth. While the Ministry of Ecology and Environment of China has employed an air pollution warning system since early 2010, the mechanism that induces the warning is kept confidential.[32] Therefore, it is unclear whether thermal inversions are correlated with air pollution warnings. To control for this channel, we exclude CFPS counties that had issued air pollution warnings just before the interview month. In the last column of Online Appendix G, we find similar result to our baseline estimate.

In the last two columns of Table A7, we add economic and demographic variables that are crucial to political trust in China (Chen, 2017; Guo, 2009). In column (9), we control for household-level income and expenditure and find no meaningful change in the baseline estimate. In column (10), we further control for age, age squared, employment status and marital status and obtain very similar results suggesting that our main findings are robust.[33]

4.3.5. Alternative choices of clustering and time trends

We next explore to what extent our baseline results are sensitive to alternative choices of clustering. Table A8 re-estimates our preferred specification under different assumptions as to the clustering of the standard errors. Column (1) is our baseline estimate, with two-way clustering and clustered standard errors at the individual and county-year-month levels. In column (2), we change the county-year-month to county-year clustering, which allows error terms to be autocorrelated within a county-year cell. In column (3), we further aggregate the clustering level from county-year to county, allowing for any autocorrelation within each county across exposure windows. In column (4), we employ two-way clustering at the county and year levels. In columns (5) and (6), we instead employ one-way clustering and cluster at county-year and county level, respectively. While all the standard errors are somewhat higher, our estimates are still highly significant at the one per cent level.

In the last two columns of Table A8, we test for robustness by replacing the provincial-specific time trend with prefecture-specific or county-specific time trends. Disaggregating the time trend at a more local level slightly increases the magnitude of the coefficient.

4.3.6. Endogenous sorting

We next address the potential threat from endogenous sorting. Air pollution may induce respondents to move, which may bias our estimates. Note, that the individual fixed effects should absorb all initial sorting based on air pollution and, therefore, only individuals who moved in our sample period can potentially bias the estimates (Deschenes et al., 2020; Fu et al., 2021). While the HRS severely limits the extent to which people move from their birthplace, 6.44 per cent of respondents moved permanently between waves. We exclude respondents who moved in different CFPS waves. The result in column (2) of Table A9 indicates a small change in the estimated coefficient. In column (3), we regress a non-local *hukou* dummy on $PM_{2.5}$ concentrations and find a small and insignificant result. In column (4), we test whether higher $PM_{2.5}$ concentrations induce educated respondents to move, as this cohort is shown to be more sensitive to air pollution. We find a small and insignificant effect.

4.3.7. Addressing bias from respondents' self-censorship

Citizens living under authoritarian regime are thought to engage in self-censorship, voicing support for the government that they oppose privately (Jiang and Yang, 2016; Shen and Truex, 2021). This phenomenon masks the true level of political trust, and, hence, may bias the estimated effect of air pollution. However, it is difficult to directly gauge the degree of self-censorship across respondents. We construct an index to assess the likelihood of self-censorship at the individual level and across time. This index involves calculating the difference in item nonresponse rates for political sensitive questions and that of non-sensitive questions. The selection of relevant questions and construction of self-censorship index is detailed in the last section of Online Appendix B. Column (2) of Table A10 reports the results with the self-censorship index as an additional control. There is only a slight change in the estimated coefficient of $PM_{2.5}$ concentrations, and the effect of the self-censorship index is small and insignificant. In column (3), we do not control for the self-censorship index but use it to weight the regression. Reassuringly, we find the almost the same estimate to our baseline finding.

4.3.8. Self-selection of local officials

Patronage networks are crucial to Chinese officials' political careers (Landry et al., 2017; Jiang, 2018). Local officials who are connected to upper-level patrons could self-select into counties with better growth potential and fewer environmental challenges, which make it easier to meet growth targets. On the other hand, higher level officials may strategically assign promising officials to specific counties for cultivating local experience, as required by the promotion guidelines from the central government. These non-random assignments of local officials may bias the estimated effect of air pollution on political trust in local government.

We take three approaches to address potential bias from leadership self-selection. First, we exclude the most and least developed counties, which are ideal locations to place favored and marginalized cadres, respectively (Landry et al., 2017). Second, we exclude

[32] We sent an inquiry to Ministry of Ecology and Environment of China, which confirmed that the mechanism that induces warnings is not disclosed to the public.

[33] These results imply that our instrument is not correlated with these socioeconomic variables. We do not include them in our baseline specification because these variables could be endogenous to air pollution (Deschenes et al., 2020).

counties with officials who are rotated quickly. The average assignment length for local officials is between three to four years (see Online Appendix A). A significantly shorter tenure suggests that officials' placement may be to cultivate local experience (Eaton and Kostka, 2014). Finally, we exclude local officials who share the same birthplace, and similar working experience, with incumbent upper-level leaders, including prefectural- and provincial-level governors and party chiefs (Jia et al., 2015).[34] All biographical information for county governors (*Qu/Xian Zhang*) and the party secretaries (*Qu/Xian Wei Shu Ji*) are from various provincial and prefectural level yearbooks and from the Baidu Encyclopedia and were collected manually.

Table A11 reports the results. In column (1), we exclude the five richest and five poorest counties using 2011 per capita real GDP. In column (2) we exclude counties which are served by officials who were rotated within two years. We further shorten the tenure to one year and exclude these officials in column (3). In the final column, we exclude officials who are potentially connected to upper-level leaders. We find the estimated effect of air pollution is between −0.1013 and −01191, which are close to our baseline estimate, implying that self-selection is unlikely to be biasing the result. Notice that, after excluding local officials with a short tenure, the coefficients of $PM_{2.5}$ concentrations increase slightly, which most likely reflects that it takes time for local citizens to evaluate incumbent officials.

5. Mechanism analysis

5.1. Evidence of direct mechanisms

Air pollution may undermine political trust by leading to clashes between local residents and government. While data on pollution-induced clashes are not available, we are able to identify local communities in which complaints or protests are arguably likely to be higher. Many studies have found that complaints and mass protests, which often involve standoffs between local residents and government officials, are more prevalent in communities close to highly polluting sources (Deng and Yang, 2013; Ahlers and Shen, 2018). In the CFPS Community/Village module, it asks: "Is there a high polluting firm, such as a chemical plant, a metallurgical refinery or a paper mill within a 5-km radius of your village/residential committee office?" If the answer is yes, it continues: "When was this highly polluting firm(s) established?" Of 621 communities surveyed across the 162 counties in CFPS, 99 or 15.94 per cent responded that they were located in the vicinity of highly polluting firms. To mitigate endogenous sorting, we limit our analysis to residents with a local *hukou* and only treat communities as being located near an industrial firm, if the industrial firm was in existence at least before 2005.[35] We then re-estimate our baseline specification depending on whether highly polluting firms are within a 5-km radius of local communities.

Table 3 reports the results. For respondents living in close vicinity to highly polluting firms, a one μg/m^3 increase in $PM_{2.5}$ concentrations reduces their political trust by 0.2001 units, or 0.076 standard deviations. It doubles the baseline estimate, despite a much smaller sample size. For the other subsample, the magnitude drops to −0.059 but remains highly significant. One may worry that the different results are attributable to demographic variables, given heterogeneity in political trust across respondents with different demographic characteristics (see Table A2). To address this concern, we augment the baseline specification with standard demographic controls in column (3) and (4) and arrive at a similar conclusion.

Note that the first-stage coefficients are higher for communities without polluting firms nearby. This pattern is similar to the first-stage results in the urban-rural heterogeneity analysis. It once again suggests that the association between thermal inversions and $PM_{2.5}$ concentrations is probably nonlinear, which is expected to be stronger at lower levels of air pollution. We use polynomial regression to flexibly estimate the effect of thermal inversions on residual $PM_{2.5}$ concentrations, which are obtained after partialling out a set of county, month, and city-by-year fixed effects. Figure A5 plots the nonlinear estimates separately for samples of high and low $PM_{2.5}$ concentrations. We find thermal inversions exert a stronger effect at lower levels of $PM_{2.5}$ concentrations and the effects become weaker for higher levels of $PM_{2.5}$ concentrations.

The mechanism through complaints or clashes, while straightforward, is limited to a small number of residents that are directly exposed to highly polluting sources. A broader mechanism is via how pollution affects people's life satisfaction, and, hence, their perception of government performance. We first examine whether, and to what extent, air pollution affects respondents' life satisfaction. In CFPS, respondents were asked "Are you satisfied with your life?" Answers were on a five-point scale with higher values indicating greater satisfaction. We regress the five-point scale on $PM_{2.5}$ concentrations using our baseline specification. Columns (1) and (2) in Table 4 report the results. In column (1), higher $PM_{2.5}$ concentrations lower the probability of expressing higher satisfaction, albeit the effect is marginally significant. In column (2), we convert the original five-point scale ratings into a dummy variable, which is set equal to one if respondents selected 4 or 5, representing high levels of satisfaction. We find that respondents living in more polluted areas are less likely to express high life satisfaction.

Addressing air pollution is the responsibility of local officials in China (Wang, 2013; Chen et al., 2018), as they have repeatedly and publicly claimed the credit for high economic growth. Failing to curb air pollution may indicate that the local government is either incompetent or irresponsible in providing a fundamental but critical public good. Consequently, local residents living in more polluted areas may be less satisfied with the performance of their local government, which reduces political trust. In CFPS, respondents were asked: "How would you rate the performance of the county/district government last year?" Answers were on a five-point scale with

[34] We use the term, similar working experience here to refer to whether local and their upper-level officials worked in the same branch of the party or of the government at the same time (Jia et al., 2015).

[35] We also use alternative cutoffs for when the firm was established and find qualitatively the same results.

Table 3
Living proximate to polluting enterprises.

	Polluting firms within 5 km radius	No polluting enterprises nearby	Polluting firms within 5 km radius	No polluting enterprises nearby
	(1)	(2)	(3)	(4)
Second Stage				
$PM_{2.5}$	−0.2001***	−0.0590***	−0.2372***	−0.0616***
	(0.0421)	(0.0177)	(0.0501)	(0.0192)
First Stage				
Accumulated Thermal Inversions	0.0147***	0.0491***	0.0137***	0.0487***
	(0.0036)	(0.0021)	(0.0037)	(0.0022)
KP *rk F*-statistic	160.75	573.5	136.56	506.2
Individual FE	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes
Other controls	No	No	Yes	Yes
No. of Obs.	28,179	76,132	24,805	66,027

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Column (1) focuses on respondents in the vicinity of highly polluting enterprises. It is directly complied from the Community/Village Questionnaire module, which asks: "Is there any highly polluting enterprise, such as a chemical plant, a metallurgical refinery or a paper mill within a 5-km radius centered at your village/residential committee office?" Columns (3) and (4) include other controls - education, income, *hukou* type, whether the respondent lives in an urban or rural area and marital status. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table 4
Life satisfaction, environmental concerns and government performance ratings.

	Life satisfaction		Performance rating		Environmental concern	
	Rating	Dummy	Rating	Dummy	Rating	Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
$PM_{2.5}$	−0.0281*	−0.0061***	0.0220***	0.0079**	0.0127	0.0068***
	(0.0149)	(0.0013)	(0.0073)	(0.0038)	(0.0172)	(0.0032)
First Stage						
Accumulated Thermal Inversions	0.0231***	0.0271***	0.0402***	0.0402***	0.0468***	0.0468***
	(0.0018)	(0.0023)	(0.0020)	(0.0020)	(0.0019)	(0.0019)
KP *rk F*-statistic	162.5	146.08	411.8	411.8	630.2	630.2
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	104,818	104,818	106,033	106,033	104,317	104,317

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006). Columns (1) and (2) focus on citizens' life satisfaction. In CFPS, respondents are asked: "Are you satisfied with your life?" Answers were on a five-point scale with higher values indicating greater life satisfaction. Responses are on a five-point scale from 1 = very unsatisfied to 5 = highly satisfied. In column (2), we recode respondents selecting options 4 and 5 as one, which refers to high life satisfaction. Columns (3) and (4) focus on the rating of local government performance. In CFPS, respondents are asked: "How would you rate the performance of the county/district government last year?" Responses are on a five-point scale from 1 = excellent to 5 = very poor. In column (4), we recode respondents selecting options 4 and 5 as one, which refers to poor performance of local government. Columns (5) and (6) focus on respondents' perceived level of environmental concern. In CFPS, respondents are asked: "How would you rate the severity of the environmental problem in China? Responses are on a 11-point scale, with higher values representing greater severity. In column (6), we convert the level of concern into a dummy variable, in which we code respondents reporting 7, 8, 9 and 10 as expressing a high level of environmental concern.

higher values expressing greater dissatisfaction. We regress the five-point scale on $PM_{2.5}$ concentrations using our baseline specification. Columns (3) and (4) in Table 4 report the results. In column (3), we find that higher $PM_{2.5}$ concentrations significantly increases the probability of expressing lower satisfaction in local government. In column (4), we convert the original ratings into a dummy variable, which is set equal to one if respondents selected 4 or 5, representing high dissatisfaction. We find that respondents living in more polluted areas are more likely to be highly dissatisfied with local government performance.

In columns (5) and (6) of Table 4, we examine how local pollution affects the level of environmental concern revealed by respondents. The question in CFPS asks: "How would you rate the severity of the environmental problem in China? Answers were on a 11-point scale, where 0 = "not severe" and 10 = "extremely severe". In column (5), we regress the 11-point scale on local air pollution. We find a positive, but not precisely estimated, effect of higher $PM_{2.5}$ concentrations on environmental concern. In column (6), we convert the original scale into a dummy variable with respondents reporting 7 to 10 defined as being concerned about the environment. We find that $PM_{2.5}$ concentrations now exert a significantly positive effect on the likelihood of being concerned about the environment. In Online Appendix H, we use alternative cutoffs for being concerned about the environment and get qualitatively the same result.

5.2. *Evidence of indirect mechanisms*

Air pollution may also undermine political trust through imposing greater health and financial burdens on citizens. A recent opinion poll by Cunningham et al. (2020) reveals that about one-third of respondents were less trusting in government if they felt that air pollution had negatively impacted their own health or the health of their immediate family members. To explore this mechanism, we first test whether higher $PM_{2.5}$ concentrations impair self-reported health. CFPS asks respondents to rate their health status on a five-point scale from 1 = excellent to 5 = poor. In column (1) of Table 5 we regress the five-point scale on local air pollution and show that higher $PM_{2.5}$ concentrations significantly increase the probability of reporting poor health. In column (2), we create a poor health dummy variable and define those reporting options 4 and 5 as being in poor health. The result remains qualitatively the same.

One concern with self-reported health data is that they may not accurately measure changes in physical health. Miller et al. (2021) argue that changes in self-reported heath may reflect evolving awareness of health problems or interactions with health professionals, rather than actual changes in physical health. As such, we exploit information on physician-diagnosed diseases to objectively measure respondents' health. The CFPS records chronic diseases diagnosed by physicians within six months preceding the interview.[36] It

Table 5
$PM_{2.5}$ effect on health.

	Self-reported health		Physician-diagnosed health	
	Ratings	Dummy	No controls	With controls
	(1)	(2)	(3)	(4)
Second Stage				
$PM_{2.5}$	0.0292***	0.0153***	0.00758***	0.00647***
	(0.00631)	(0.00243)	(0.00222)	(0.00222)
First Stage				
Accumulated Thermal Inversions	0.0407***	0.0407***	0.0401***	0.0400***
	(0.00177)	(0.00177)	(0.00197)	(0.00197)
KP F-statistic	530.6	530.6	414.8	411.9
Individual FE	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes
Demographic controls	No	No	No	Yes
No. of Obs.	106,033	106,033	106,033	90,832

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006). In column (1), the dependent variable is self-reported health status. In CFPS, respondents are asked to rate their health status, with five options being provided: 1 = excellent; 2 = very good; 3 = good; 4 = fair and 5 = poor. In column (2), we define a poor health dummy as 1 when respondents report having either fair or poor health. For columns (3) and (4), the dependent variable is a dummy variable indicating whether the respondent had been diagnosed with an air pollution related chronic disease within six months prior to the interview. Demographic controls include age, education, income and daily smoking pattern (smoking or not and, if yes how many cigarettes per day).

[36] The original questions in CFPS are: "During the past six months, have you had any doctor-diagnosed chronic disease?" If the answer is yes, it continues: "What was your doctor's diagnosis of the disease you suffered from?"

enables us to isolate the diseases that are more relevant to air pollution. Online Appendix I reproduces these chronic diseases, most of which are attached to respiratory and circulatory systems. In column (3) of Table 5, we find that higher $PM_{2.5}$ concentrations significantly increase the probability of being diagnosed with air pollution related chronic diseases. In Column (4), we obtain a similar result after including age, education, income and smoking behavior that strongly predict healthcare utilization. Compared to self-reported health, chronic diseases appear to be less responsive to air pollution, reflecting their serious nature and more complicated causes.

Poor health contributes to higher healthcare expenditure, potentially crowding out consumption, reducing welfare and undermining citizens' political trust. To capture the healthcare related financial burden, we focus on out-of-pocket medical expenditure defined as the direct medical costs borne by individuals, for which they cannot seek reimbursement. These out-of-pocket expenses have been identified as one of the most important causes of household impoverishment in China (Wagstaff and Lindelow, 2008). We regress the total out-of-pocket medical expenditure, if any, in logarithm form on $PM_{2.5}$ concentrations.[37] Note, that this measure includes all medical expenditure and not just medical expenditure related to health problems that are related to air pollution, for which we do not have the data.

Table 6 reports the results. In column (1), we find that a one $\mu g/m^3$ increase in $PM_{2.5}$ concentrations increases out-of-pocket medical expenditure by 1.9 per cent. In column (2), we include controls for age, education, income and smoking behavior that are strongly related to healthcare utilization and find almost the same result. Note that our estimated effect is half that which is reported in Yang and Zhang (2018). Our lower estimates possibly might reflect that their estimates were for total medical expenditure and urban residents in China.

Finally, poor health also implies lower labor productivity, and therefore, less income, which may further undermine political trust. Existing studies have consistently shown that air pollution impairs labor productivity at the individual level (see e.g. Graff Zivin and Neidell, 2016; Chang et al., 2016; Chang et al., 2019; He et al., 2019). However, we are unable to construct a direct measure of individual-level labor productivity, as working hours, particularly for those participating in farming jobs, are not recorded in CFPS. Income is measured at the household level for rural households. We estimate the causal effect of $PM_{2.5}$ concentrations on household income, using the same instrument strategy. Using household income has the major advantage that it captures intra household spillovers, as health members may reduce labor supply to care for other members of the household, which is encouraged in Confucian culture.

Table 7 reports the results. In Column (1) we find that air pollution reduces household income, although the effect is marginally significant. Columns (2) and (3) further demonstrate that the negative effect is driven by rural households, which are disproportionally exposed to pollution, but possess limited resources to defend against it and often fail to recognize the associated health risks.

Overall, we find that respondents exposed to high level of $PM_{2.5}$ concentrations are more likely to report being in poor health, be diagnosed with chronic diseases and spend significantly more out-of-pocket medical expenditure. We also find a dampening effect on household income, although the effect is less significant. These negative outcomes adversely affect respondents' welfare and make them less trusting in local government.

6. Discussion of the economic significance

We take three approaches to demonstrate the economic significance of our findings. First, we show whether, and to what extent, lower levels of political trust could impede local officials' prospects of being promoted. Second, we compare the estimated effect of air pollution to that of economic growth, which underpins support for the regime, from existing studies. Third, we combine our baseline estimate with the target abatement set by national environmental legislation and simulate the potential gains pertaining to political trust.

While evaluation of the performance of local officials rests with higher-level government (see Online Appendix A), local officials' chances of being promoted are influenced, to a certain extent, by the attitude of local citizens. Reinforcing this point, central government has increasingly emphasized the role of local opinions during the cadre selection process (Wang, 2013). Existing studies have documented qualitative evidence that endorsement from local citizens is positively associated with the incumbents' chance of being promoted (Chen, 2017; Ma, 2019). However, to our knowledge, no existing studies have quantified the effect.

We use hand collected biographical information for both county governors (*Qu/Xian Zhang*) and party secretaries (*Qu/Xian Wei Shu Ji*) in the counties surveyed in CFPS from various provincial and prefectural level yearbooks and the Baidu Encyclopedia. Our dataset contains information on the careers of these local officials, as well as important demographic data on the officials including age, gender, education, birthplace and their career profiles.

We use the following model to estimate the relationship between local citizens' political trust and whether local officials were promoted:

$$\mathrm{Pr}omotion_{ictp} = Trust_{jct-1} + X'\beta + \alpha_i + \gamma_c + \lambda_t + \mathrm{Pr}ov\_trend_p + \varepsilon_{ictp} \tag{4}$$

We define political promotion as follows:

[37] The original question in CFPS is: "In the past 12 months, the total direct medical expenditure (excluding what was reimbursed or reimbursable but including what was paid by or borrowed from relatives) was__RMB?" We replace zero expenditure with one before taking logarithm transformation. In our sample, 95 per cent of respondents reported having non-zero out-of-pocket medical expenditure. The mean out-of-pocket medical expenditure was 2842 RMB, accounting for 14.39 per cent of net per capita annual income.

Table 6
Effect of $PM_{2.5}$ effect on out-of-pocket medical expenditure.

	Baseline	More controls
	(1)	(2)
Second Stage		
PM2.5	0.0190**	0.0184**
	(0.00847)	(0.00854)
First Stage		
Accumulated Thermal Inversions	0.0745***	0.0746***
	(0.00185)	(0.00186)
KP F-statistic	1614.3	1608.9
Individual FE	Yes	Yes
County-by-Year FE	Yes	Yes
Weather controls	Yes	Yes
Provincial-specific time trend	Yes	Yes
No. of Obs.	57,921	56,825

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is total out-of-medical expenditure, if any, in logarithm form. In our sample, less than five per cent of respondents reported having zero out-of-pocket medical expenditure. We replace zero expenditure with one before taking the logarithm transformation. Using a Heckman selection model or directly omitting zero expenditure respondents does not qualitatively alter our finding. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006). Column (1) is our baseline specification, while column (2) controls for age, education and daily smoking pattern (smoking or not and, if yes how many cigarettes per day).

Table 7
Effect of PM2.5 effect on household income.

	All households	Urban households	Rural households
	(1)	(2)	(3)
Second Stage			
$PM_{2.5}$	0.0123*	0.0094	0.0147**
	(0.0062)	(0.0109)	(0.0065)
First Stage			
Accumulated Thermal Inversions	0.0195***	0.0298***	0.0593***
	(0.0061)	(0.0071)	(0.0076)
KP *rk F*-statistic	110.41	107.58	161.53
Household FE	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes
No. of Obs.	47,356	21,519	25,837

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The dependent variable is household income in logarithm form. We use prefectural-level CPI to remove any price effect. Household income is defined for the 12 months preceding the interview month. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the same 12-months exposure window. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Promotion = { 1: if a county governor is promoted to party secretary in another location; *or*
if a party secretary is promoted to prefectural level governor *or*
if a county official is promoted to a district-level official.
0 : moves to the same or equivalent position in other county (district) }

$Promotion_{ictp} = 1$, if local official i from county (or district) c located in province p was promoted in year t. This definition of promotion follows the approach used by Jia et al. (2015), $Trust_{jct-1}$ is political trust as revealed by CFPS respondent j from the same county (or district). To mitigate endogeneity issues, we lagged political trust by one year. We control for various fixed effects at the official, county (or district) and year levels, as well as including a provincial-specific time trend, depending on the specification.

Table A12 reports the results. We find that if political trust is lower by one unit, this reduces the probability of being promoted by 0.0134 and 0.0073 per cent, respectively for county governor and party secretary. However, this result is only significant, albeit marginally, for county governor. Combining our baseline estimate (−0.1064) with a one standard deviation increase in $PM_{2.5}$ concentrations (24.520) would lower a county governor's chance of being promoted by 0.035 per cent.[38]

Next, we compared the effect of air pollution to that of economic performance from established studies. Most studies maintain that government performance, particularly in terms of ensuring economic growth, is crucial to maintaining political trust in China. Dong and Kübler (2018) and Chen (2017) estimate the effect of local government performance on trust in local government. Dong and Kübler (2018), based on a survey conducted in Sichuan province between 2014 and 2016, find that a one-unit reduction in perceived government performance is associated with 0.51 units lower trust in local government. Using the 2012 Asian Barometer Survey, Chen (2017) finds that a one-unit reduction in perceived economic performance is associated with 0.41 units lower trust in local government. Compared to those studies, our baseline effect of air pollution is equivalent to around 20 per cent of the estimated relationship between government/economic performance and trust in local government.[39] We also estimate the association between county-level economic growth and trust in local government. We find that a one unit increase in economic growth at the county level is associated with 0.637 points higher trust in local government. This result implies that the baseline estimate of $PM_{2.5}$ concentrations is 16.7 per cent of the estimated growth–trust relationship.[40] These comparisons, while straightforward, are only suggestive as endogeneity of local government/economic performance is not considered.

As another way to demonstrate economic significance of our baseline result, we compare the effect of air pollution to historical shocks that permanently reshape trust in local government. Chen and Yang (2019) use CFPS2012 and document that respondents who experienced the Great Chinese Famine have, on average, 0.434 points lower trust in local government. This finding implies that contemporary air pollution exerts 24.5 per cent of the negative effect stemming from one of the most traumatic famines in human history. However, it should be highlighted that our finding is arguably weaker because of its transitory nature.

What do our baseline results suggest for the effectiveness of government legislation designed to improve air quality? In 2013, China enacted the "Air Pollution Prevention and Control Action Plan", which is its toughest-ever legislation designed to improve air quality. Based on an integrated assessment model, Zhang et al. (2019) attribute a nationwide reduction in $PM_{2.5}$ concentrations of 16 $\mu g/m^3$ to the legislation.[41] Our baseline estimate suggests that it would translate into 34 per cent higher trust in local government evaluated at the mean. In 2018, the central government issued the "Three-year Action Plan for Cleaner Air". One target of the plan is to reduce $PM_{2.5}$ concentrations by at least 18 per cent among cities that have failed to meet annual standard of 35 $\mu g/m^3$ (State Council, 2018). Combining our baseline estimate with the $PM_{2.5}$ concentrations from ground monitors, we project that trust in local government would increase by 17 per cent among counties that have met the abatement target.

7. Conclusion

We have estimated the causal effect of $PM_{2.5}$ on trust in local government in China. Combining data from the CFPS with satellite derived $PM_{2.5}$ concentrations, we exploit exogeneous variations due to thermal inversions and find that a one $\mu g/m^3$ increase in $PM_{2.5}$ reduces trust in local government by 4.1 per cent of one standard deviation. This result is robust to a number of sensitivity checks. We probe the mechanisms underlying our main result. We find that the effect of $PM_{2.5}$ concentrations on political trust is stronger for respondents living in close vicinity to highly polluting firms and find that prolonged exposure to $PM_{2.5}$ impairs respondents' life satisfaction and evaluation of local government performance, increases concern about the environment, adversely affects their health and increases out-of-pocket medical expenses. Finally, we also find suggestive evidence that air pollution dampens household income, which affects economic welfare and, hence, political trust.

Our results have implications not only for China but for other developing countries. Over four billion people in developing countries are currently exposed to similar levels of air pollution as in China. Civil society and democratic values are arguably fragile in many developing countries (see eg. Acemoglu and Robinson, 2006). Our finding that air pollution reduces political trust in a setting in which local officials are largely unaccountable to citizens, suggests the potential for air pollution to generate social unrest, not only in China, but also in other authoritarian regimes and nascent democracies which have relied primarily on fossil-fuel driven economic growth for political legitimacy.

Although our paper is the first to examine the causal effect of air pollution on political trust using a large and nationally representative survey, it shares a caveat with much of the related literature that it relies on self-reported information on political trust. In addition to self-censorship, respondents might have different understandings of what constitutes political trust and standards of trust. Future studies could use laboratory experiments or field experiments paired with better surveys to address this limitation with using survey data.

Another caveat is that different pollutants are highly correlated, which prevents us from isolating the effect of a single pollutant

[38] The chance of being promoted is, on average, 3.8 per cent for a county governor in CFPS counties over the period 2010–2019.

[39] Chen (2017) and Dong and Kübler (2018) do not provide detailed summary statistics; hence, we cannot convert their estimated coefficients into elasticity form.

[40] County-level economic growth is compiled from the China County-Level Economic Research Database. Full estimates are results are available upon request.

[41] Among the 16 $\mu g/m^3$ reduction in $PM_{2.5}$ concentration, 11 $\mu g/m^3$ is due to strengthening industrial emission standards, 2.8 $\mu g/m^3$ due to phasing out outdated industrial capacities and 2.2 $\mu g/m^3$ due to promoting clean fuels in the residential sector.

(Godzinski and Castillo, 2021). While this issue is ameliorated by the fact that not all air pollutants are affected by thermal inversions, other air pollutants such as carbon monoxide are also highly responsive to this atmospheric phenomenon (Arceo et al., 2016). Therefore, our estimates can be interpreted as the effect of air pollution on political trust more broadly, rather than specifically from particulate matters. Future studies could identify the criteria pollutant that has the largest negative effect on political trust.

Declaration of competing interest

None.

Compliance with Ethical Standards: The authors have no relevant financial interests to disclose.

Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102724.

Appendix

Table A1
Summary Statistics for key variables

Individual level	Mean	Std. Dev.	Min	Max
Trust in local government	5.008	2.623	0	10
Trust in parents	9.291	1.497	0	10
Trust in neighborhood	6.589	2.179	0	10
Trust in Americans	2.357	2.491	0	10
Trust in strangers	2.074	2.139	0	10
Trust in doctors	6.743	2.338	0	10
Level of environmental concern	6.382	2.736	0	10
Male (Yes = 1)	0.489	0.500	0	1
Marriage (Yes = 1)	0.809	0.393	0	1
Conflict with local officials (Yes = 1)	0.040	0.195	0	1
Urban *Hukou* (Yes = 1)	0.273	0.273	0	1
Urban Residence (Yes = 1)	0.469	0.499	0	1
CCP membership (Yes = 1)	0.064	0.244	0	1
No. of schooling years	7.152	4.876	0	22
Age	46.740	15.970	18	98
Self-reported health status	3.082	1.226	1	5
Self-reported relative income status in local area	2.517	1.0480	1	5
County level				
Monthly average PM2.5 concentrations (μg/m^3)	45.260	24.520	0.130	209.000
Monthly average occurrences of Thermal Inversions	40.480	22.560	0	120

Notes: Individual panel sample size is 106,033 containing 33,219 individuals. The county-month panel covers 162 counties over the period from 2010 to 2019, with a sample size of 19,560. All trust variables are measured between zero and 10, where 0 refers to no trust at all and 10 is an extremely high level of trust. Level of environmental concern is also scaled between zero and 10, and in ascending order of concern. Self-reported health status contains five categories: 1 = Excellent; 2 = Very good; 3 = Good; 4 = Fair and 5 = Poor. Self-reported income status is defined on a five-point scale, where 1 indicates the lowest and 5 the highest.

Table A2
Political trust in local government by different cohorts

	Mean	Std. Dev.	Min	Max
Trust in local government	5.008	2.623	0	10
Trust in local government (male)	4.951	2.643	0	10
Trust in local government (female)	5.063	2.602	0	10
Trust in local government (urban, residence = 1)	4.744	2.553	0	10
Trust in local government (rural)	5.247	2.660	0	10
Trust in local government (with high school degree and above)	4.735	2.395	0	10
Trust in local government (below high school degree)	5.072	2.676	0	10
Trust in local government (age $\geq$ 55)	5.509	2.648	0	10
Trust in local government (age<55)	4.737	2.576	0	10
Trust in local government (married)	4.984	2.633	0	10
Trust in local government (no married)	5.109	2.575	0	10
Trust in local government (CCP member)	5.430	2.416	0	10
Trust in local government (non CCP member)	4.964	2.636	0	10
Trust in local government (health)	5.158	2.638	0	10
Trust in local government (not health)	4.952	2.714	0	10
Trust in local government (high relative income)	4.639	2.690	0	10
Trust in local government (low relative income)	5.275	2.547	0	10

Notes: Individual panel sample size is 106,033 containing 33,219 individuals. All trust variables are measured between zero and 10, where 0 refers to no trust at all and 10 is an extremely high level of trust. Urban and rural divide is based on residential areas of respondents. Health refers to those respondents reporting Excellent, very good and good health conditions. High relative income refers to respondents reporting that their income is above the local average level.

Table A3
Selecting the optimal length of exposure window

Maximum lag (Month)	OLS estimations		2SLS estimations									
	AIC	BIC	LLC	AIC	Log AIC	SIC	Log SIC	FPE	HQ	Rice	Shibata	GCV
1M	417660.3	417780.6	−361.365	42.1984	3.7424	63.317	4.1482	42.2906	49.7536	44.5768	40.6803	43.2354
2M	417661.3	417770.9	−356.781	37.6329	3.6279	53.8345	3.9859	37.6892	43.5193	39.2241	36.5548	38.3415
3M	417657.3	417759.4	−346.286	33.6134	3.5149	52.9018	3.9684	33.7164	40.407	36.0756	32.1367	34.6625
4M	417656.2	417749.4	−340.568	30.9656	3.4329	49.9118	3.9103	31.0764	37.5864	33.5318	29.475	32.0456
5M	417653.2	417731	−332.339	25.919	3.255	39.83	3.6846	25.9864	30.8571	27.589	24.8854	26.639
6M	417654.4	417738.2	−322.962	23.1981	3.1441	38.295	3.6453	23.2944	28.4322	25.3638	21.9807	24.098
7M	417652.1	417720.2	−321.044	20.5683	3.0237	30.134	3.4057	20.6057	24.017	21.576	19.9054	21.0124
8M	417653.7	417708.6	**−270.157**	7.0109	1.9475	7.8996	2.0668	7.0113	7.3589	7.0391	6.9859	7.076
9M	417654.1	417705.2	−271.617	7.0672	1.9555	7.7752	2.0509	7.0674	7.3465	7.0852	7.0509	7.08
10M	**417651.2**	417699.5	−272.682	7.0751	1.9566	7.6003	2.0282	**6.8157**	**6.9491**	7.0851	7.0658	**6.8178**
11M	417656.1	**417689**	−271.534	**6.8157**	**1.9192**	**7.149**	**1.967**	7.0752	7.2838	**6.8199**	**6.8117**	7.0246
12M	417658.2	417792.2	−320.774	17.813	2.8799	21.5608	3.0709	17.817	19.2485	18.0042	17.6557	17.9036
13M	417658.9	417802.5	−330.865	20.8643	3.038	24.6585	3.2051	20.8674	22.3283	21.0334	20.7217	20.945
14M	417657.8	417810.9	−474.776	263.914	5.5756	327.159	5.7904	263.999	287.959	267.555	260.9999	265.626
15M	417658.8	417821.5	−518.452	615.328	6.4222	859.474	6.7563	616.075	704.713	637.593	599.7957	625.3427
16M	417660.3	417832.6	−560.721	1116.70	7.0181	1288.64	7.1613	1116.80	1183.54	1123.26	1111.025	1119.852
17M	417651.6	417833.5	−709.362	15879.3	9.6728	20160.1	9.9115	15886.2	17494.7	16153.8	15665.22	16007.28
18M	417651.6	417843	−821.462	113519	11.6397	147603	11.9023	113586	126286	115932	111688.9	114634.7
19M	417652.2	417853.2	−617.662	3336.78	8.1128	4443.47	8.3992	3339.33	3748.17	3422.54	3273.479	3376.089
20M	417654	417864.6	−677.092	9544.67	9.1637	13017.3	9.474	9553.94	10825.8	9837.41	9334.568	9677.613

Note: AIC refers to Akaike Information Criterion; BIC refers to Bayesian Information Criterion; SIC refers to Schwarz Information Criterion; FPE refers to Amemiya Prediction Criterion; HQ refers to Hannan-Quinn Criterion; Rice refers to Rice Criterion; Shibata refers to Shibata Criterion. For OLS results, we use the building-in STATA code "*ic*"; for 2SLS results, we use the user-written program "*diagreg2*"

Table A4
Cumulative versus individual month's $PM_{2.5}$ effects

	Baseline	Individual month	Both included
	(1)	(2)	(3)
Second Stage			
$PM_{2.5}$ (cumulative)	−0.1064***		−0.0959***
	(0.028)		(0.0275)
$PM_{2.5}$ (single month)		−0.0083***	−0.0079
		(0.00261)	(0.00563)
First Stage			
Thermal Inversions (1st to 11th months)	0.0308***		0.0275***
	(0.002)		(0.00192)
Thermal Inversions (11th month)		0.335***	0.0566***
		(0.0203)	(0.00320)
KP *rk F*-statistic	237.8	272.4	38.25
Individual FE	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes
No. of Obs.	106,033	106,033	106,033

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Column (2) uses the $PM_{2.5}$ concertation in the 11th month before the interview month. Its instrument is county-level mean $PM_{2.5}$ concentrations in the 11th month preceding the interview. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A5
Excluding categories of respondents

	Baseline	Excluding conflict experience	Excluding negative experience	Excluding certain family background	Excluding CCP members	Excluding HAP	Transboundary $PM_{2.5}$ excluded
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Second Stage							
$PM_{2.5}$	−0.1064***	−0.1050***	−0.0989***	−0.103***	−0.137***	−0.226***	−0.1048***
	(0.028)	(0.0261)	(0.033)	(0.0260)	(0.0423)	(0.0615)	(0.029)
First Stage							
Accumulated Thermal Inversions	0.0308***	0.0337***	0.0303***	0.0333***	0.0223***	0.0190***	0.0291***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
KP *rk F*-statistic	237.8	273.8	210.4	283.2	151.5	55.60	246.3
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	106,033	94,769	74,657	102,543	97,601	63,045	97,522

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The number of observations differ depending on the sample considered. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is the total number of thermal inversion occurrences in the same period. Weather controls consist of ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. The respondents excluded in each column are defined in context. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A6
Effect of air pollution on trust in other groups and controlling for generalized trust

	Baseline	Control trust in strangers	Control trust in neighborhood	Trust in parents	Trust in doctors	Trust in Americans
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
PM2.5	−0.1064***	−0.1196***	−0.0925***	−0.0171	−0.0185	0.0010
	(0.028)	(0.039)	(0.033)	(0.015)	(0.035)	(0.032)
Trust in strangers		0.2216***				
		(0.005)				
Trust in neighborhood			0.2919***			
			(0.005)			
First Stage						
Accumulated Thermal Inversions	0.0308***	0.0227***	0.0261***	0.0316***	0.0237***	0.0293***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
KP F-statistic	237.8	151.8	181.9	254.6	162.8	212.0
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	106,033	105,672	105,918	106,033	106,033	103,484

Note: **$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The number of observations is based upon the sample considered. The dependent variable is individual-level trust in strangers, neighbors, parents, doctors, and Americans. Similar to political trust in local government, these trust variables are measured on a 0–10 scale, with 0 indicating extreme distrust, and 10 indicating extreme trust. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls include ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A7
Checks on the validity of our instrument

	Baseline	IV-LIML Estimator	71st layer (340m)	69th layer (640m)	TI Strength	Official $PM_{2.5}$ Data	Official AQI	Low TI counties removed	Income & Expenditure	other controls Included
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Second Stage										
$PM_{2.5}$	−0.1064***	−0.1120***	−0.1141***	−0.0737***	−0.1120***	−0.1089***	−0.0499***	−0.1312***	−0.1080***	−0.1151***
	(0.028)	(0.031)	(0.031)	(0.021)	(0.037)	(0.040)	(0.0180)	(0.0419)	(0.039)	(0.032)
First Stage										
Accumulated Thermal Inversions	0.0308***	0.0280***	0.0304***	0.0457***		0.0274***	0.0585***	0.0226***	0.0267***	0.0336***
	(0.002)	(0.0020)	(0.003)	(0.0024)		(0.0042)	(0.0050)	(0.0021)	(0.0022)	(0.0025)
Thermal Inversions strengths					1.402***					
					(0.144)					
KP *rk F*-statistic	237.8	193.2	123.7	366.2	94.88	42.34	139.3	117.8	151.7	174.7
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	106,033	106,033	106,033	106,033	106,033	73,647	74,657	100,470	72,815	73,340

Note: **p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The number of observations is based upon the sample considered. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. TI strength refers to the cumulative temperature differences in the exposure window. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A8
Alternative choices of clustering and time trends

	Baseline	Individual & County-year	Individual & County	County & Year	County-Year (One way)	County (One way)	City-specific time trend	County-specific time trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
$PM_{2.5}$	−0.1064***	−0.1064***	−0.1064***	−0.1064***	−0.1064***	−0.1064***	−0.1370***	−0.1140***
	(0.028)	(0.0299)	(0.0303)	(0.0300)	(0.0318)	(0.0363)	(0.038)	(0.030)
First Stage								
Accumulated Thermal Inversions	0.0308***	0.0308***	0.0308***	0.0308***	0.0308***	0.0308***	0.0237***	0.0290***
	(0.002)	(0.00259)	(0.00356)	(0.00425)	(0.0318)	(0.0363)	(0.002)	(0.002)
KP *rk F*-statistic	237.8	141.4	74.82	52.35	108.3	53.42	166.6	229.8
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	No	No
City-specific time trend	No	No	No	No	No	No	Yes	No
County-specific time trend	No	No	No	No	No	No	No	Yes
No. of Obs.	106,033	106,033	106,033	106,033	106,033	106,033	106,033	106,033

Note: **p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The number of observations is based upon the sample considered. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A9
Test for endogenous sorting

	Baseline	Excluding movers	Non-local Hukou = 1	Educated respondents = 1
	(1)	(2)	(1)	(2)
Second Stage				
$PM_{2.5}$	−0.1064***	−0.115***	0.00387	0.00607
	(0.028)	(0.035)	(0.00644)	(0.0328)
First Stage				
Accumulated Thermal Inversions	0.0308***	0.0275***	0.0218***	0.0164***
	(0.002)	(0.002)	(0.00227)	(0.00226)
KP *rk F*-statistic	237.8	139.0	92.11	52.37
Individual FE	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes
No. of Obs.	106,033	85,546	106,033	100,101

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. Educated respondents refers to individuals holding at least high school qualifications. Weather controls include ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald *rk F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A10
Addressing self-censorship across respondents

	Baseline	Index controlled	Index weighted
	(1)	(2)	(3)
Second Stage			
$PM_{2.5}$	−0.1064***	−0.1051***	−0.1051***
	(0.028)	(0.028)	(0.028)
Self-censorship index		0.0039	0.0039
		(0.138)	(0.138)
First Stage			
Thermal Inversions	0.0308***	0.0286***	0.0286***
	(0.002)	(0.002)	(0.002)
KP *rk F*-statistic	237.8	198.9	198.9
Individual FE	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes
No. of Obs.	106,033	103,219	103,219

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is total number of thermal inversion occurrences in the same period. The construction of the self-censorship index is described in the last section of Online Appendix B. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk F*-statistic is the Kleibergen-Paap Wald rk *F* statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

Table A11
Addressing leadership self-selection

	(1)	(2)	(3)	(4)
Second Stage				
$PM_{2.5}$	−0.1013***	−0.1144***	−0.1231***	−0.1191***
	(0.022)	(0.021)	(0.021)	(0.023)
First Stage				
Thermal Inversions	0.0261***	0.0314***	0.0333***	0.0298***
	(0.001)	(0.002)	(0.002)	(0.002)
KP *rk F*-statistic	168.4	213.7	240.1	204.8
Individual FE	Yes	Yes	Yes	Yes
County-by-Year FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Provincial-specific time trend	Yes	Yes	Yes	Yes
No. of Obs.	94,309	100,137	103,219	100,448

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the individual and county-year-month levels. The dependent variable is individual-level political trust in local government. The key explanatory variable is county-level mean $PM_{2.5}$ concentrations in the 11 months preceding the interview. Its instrument is the total number of thermal inversion occurrences in the same period. Weather controls are ten 6 °C wide bins (ranging from below −12 °C to above 32 °C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP *rk* F-statistic is the Kleibergen-Paap Wald *rk* F statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006). Column (1) removes the five richest and five poorest counties (in terms of real GDP per capita in 2011). Column (2) excludes the counties with officials who had tenure for less than two years. Column (3) further shortens the tenure to one year. Column (4) excludes local officials who share the same birthplace and similar career profiles with the incumbent prefectural- and provincial-level county governors and party secretaries.

Table A12
Citizens' political trust and local officials' chance of promotion

	County governor		Party secretary	
	(1)	(2)	(3)	(4)
Political trust	0.0134*	0.0134*	0.0072	0.0073
	(0.006)	(0.007)	(0.009)	(0.009)
No. of Obs.	106,033	106,033	106,033	106,033
Demographic controls	Yes	Yes	Yes	Yes
Official FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Provincial specific time trend	No	Yes	No	Yes

Notes: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the official and county-year levels. Political trust in local government is scaled between 0 and 10, where 0 indicates no trust at all and 10 extremely high trust. Demographic controls of local officials contain age, gender, education and whether the official is indigenous to his or her governing county.

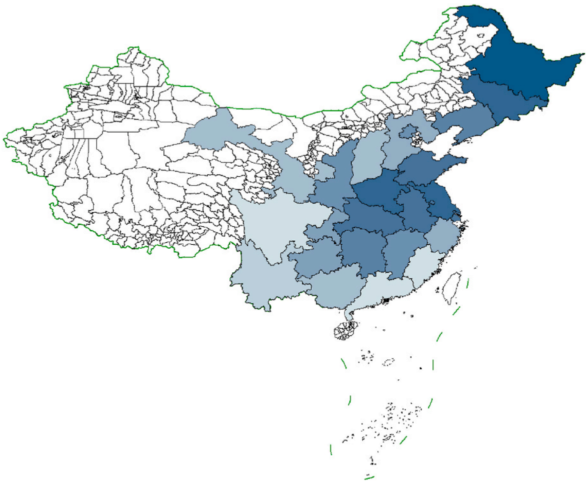


Fig. A1. CFPS surveyed areas and the changes in mean $PM_{2.5}$ concentrations over the period of 2010–2019, Note: To capture the changes in $PM_{2.5}$ reductions over the period 2010–2019, we use the difference between the mean concentrations from 2010 to 2012 and the mean concentrations from 2017 to 2019. The darker the color, the greater the reductions in $PM_{2.5}$. Because we are not allowed to disclose the precise locations of CFPS counties under the terms of the license agreement, we can only highlight the provinces with which counties surveyed in CFPS are affiliated.

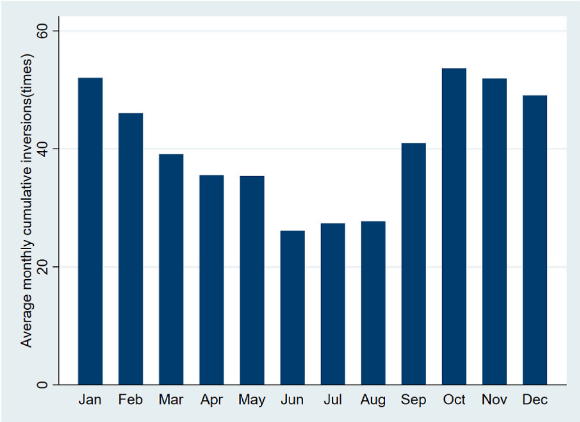


Fig. A2. Average number of thermal inversions for each month of the year, Note: Thermal inversion is defined for the temperature differences between the 72nd layer (110m) and the 70th layer (550m). We aggregate the occurrences of the thermal inversion across all 6-h periods within a month.

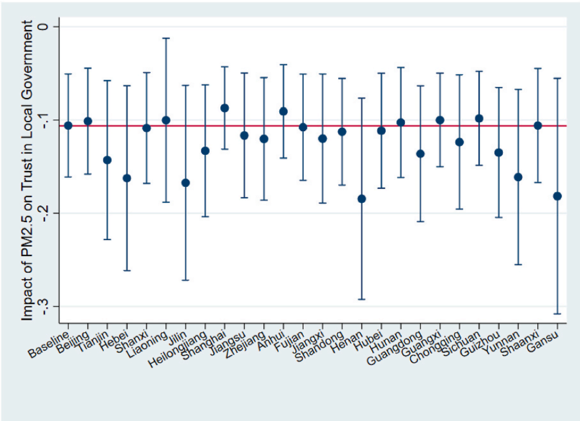


Fig. A3. Excluding one province/municipality in each regression, Note: Each dot refers to one 2SLS point estimate corresponding to the province dropped. The whiskers denote 95% confidence intervals and the red horizontal line marks the baseline estimate.

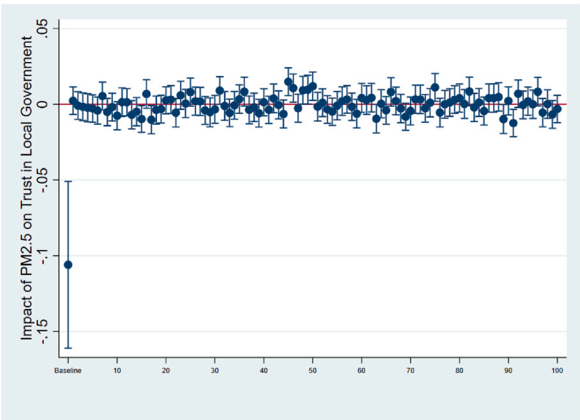
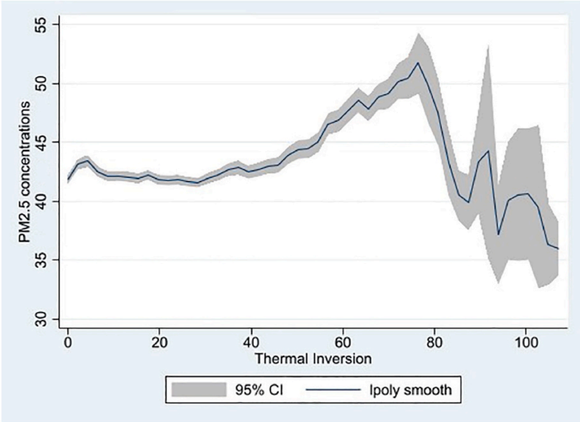


Fig. A4. Placebo test reassigning pollution data randomly to a different period's inversion and weather data, Note: Each dot refers to one 2SLS point estimate corresponding to a round of data randomization process. The whiskers denote 95% confidence intervals.



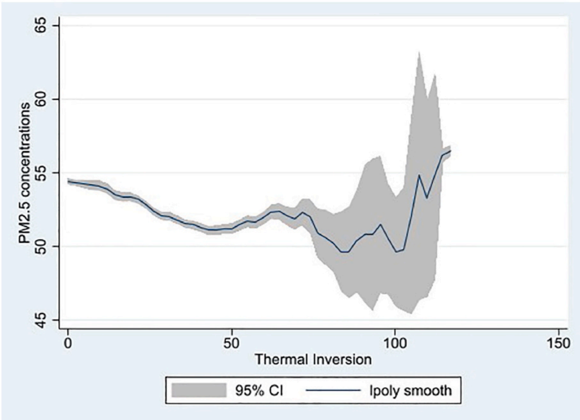


Fig. A5. Nonlinear estimates between thermal inversion and $PM_{2.5}$ concentrations, above and below median $PM_{2.5}$ concentrations. Note: counties below median $PM_{2.5}$ concentrations. Note: counties above median $PM_{2.5}$ concentrations.

References

Acemoglu, D., Robinson, J.A., 2006. Economic Origins of Dictatorship and Democracy. Cambridge University Press.

Abdul-Wahab, S.A., Bakheit, C.S., Siddiqui, R.A., 2005. Study the relationship between the health effects and characterization of thermal inversions in the Sultanate of Oman. Atmos. Environ. 39 (30), 5466–5471.

Ahlers, A.L., Shen, Y., 2018. Breathe easy? local nuances of authoritarian environmentalism in China's battle against air pollution. China Q. 234, 299–319.

Alkon, M., Wang, E.H., 2018. Pollution lowers support for China's regime: quasi-experimental evidence from Beijing. J. Polit. 80 (1), 327–331.

Almond, D., Mazumder, B., van Ewijk, R., 2014. In utero Ramadan exposure and children's academic performance. Econ. J. 125 (589), 1501–1533.

Angrist, J.D., Krueger, A.B., 2001. Instrumental variables and the search for identification: from supply and demand to natural experiments. J. Econ. Perspect. 15 (4), 69–85.

Annual Report on the Development of China's Rule of Law No12, 2014. Annual Report on the Development of China's Rule of Law (In Chinese). Social Science Academic Press (China) press, Beijing.

Arceo, E., Hanna, R., Oliva, P., 2016. Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. Econ. J. 126 (591), 257–280.

Barwick, P.J., Li, S., Rao, D., Zahur, N Bin, 2018. The Morbidity Cost of Air Pollution: Evidence from Consumer Spending in China. NBER Working Paper.

Bondy, M., Roth, S., Sager, L., 2020. Crime is in the air: the contemporaneous relationship between air pollution and crime. J. Assoc. Environ. Resour. Econ. 7 (3), 555–585.

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J.D., O'Dell, K., Pierce, J.R., 2019. The effect of pollution on crime: evidence from data on particulate matter and ozone. J. Environ. Econ. Manag. 98, 102267 https://doi.org/10.1016/j.jeem.2019.102267.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M., 2016. Particulate pollution and the productivity of pear packers. Am. Econ. J. Econ. Pol. 8 (3), 141–169.

Chang, T.Y., Huang, W., Wang, Y., 2018. Something in the air: pollution and the demand for health insurance. Rev. Econ. Stud. 85 (3), 1609–1634.

Chang, T.Y., Graff Zivin, J., Gross, T., Neidell, M., 2019. The effect of pollution on worker productivity: evidence from call center workers in China. Am. Econ. J. Appl. Econ. 11 (1), 151–172.

Chen, D., 2017. Local distrust and regime support: sources and effects of political trust in China. Polit. Res. Q. 70 (2), 314–326.

Chen, S., Oliva, P., Zhang, P., 2022. The effect of air pollution on migration: evidence from China. J. Dev. Econ. 156, 102833 https://doi.org/10.1016/j.jdeveco.2022.102833.

Chen, Y.J., Li, P., Lu, Y., 2018. Career concerns and multitasking local bureaucrats: evidence of a target-based performance evaluation system in China. J. Dev. Econ. 133, 84–101.

Chen, Y., Yang, D.Y., 2019. Historical Traumas and the Roots of Political Distrust: Political Inference from the Great Chinese Famine. NEBR working paper.

Coleman, S.J., 1990. Foundations of Social Theory. The Belknap Press of Harvard University Press, Cambridge, MA.
Cunningham, E., Saich, T., Turiel, J., 2020. Understanding CCP Resilience: Surveying Chinese Public Opinion through Time. Ash Center for Democratic Governance and Innovation. Harvard Kennedy School. Retrieved from. https://ash.harvard.edu/publications/understanding-ccp-resilience-surveying-chinese-public-opinion-through-time.
Deng, Y., Yang, G., 2013. Pollution and protest in China: environmental mobilization in context. China Q. 214, 321–336.
Deryugina, T., Heutel, G., Miller, N.H., Molitor, D., Reif, J., 2019. The mortality and medical costs of air Pollution: evidence from changes in wind direction. Am. Econ. Rev. 109 (12), 4178–4219.
Deschenes, O., Greenstone, M., Shapiro, J.S., 2017. Defensive investments and the demand for air quality: evidence from the NOx Budget Program. Am. Econ. Rev. 107 (10), 2958–2989.
Deschenes, O., Wang, H., Wang, S., Zhang, P., 2020. The effect of air pollution on body weight and obesity: evidence from China. J. Dev. Econ. 145 https://doi.org/10.1016/j.jdeveco.2020.102461.
Dong, L., Kübler, D., 2018. Sources of local political trust in rural China. J. Contemp. China 27 (110), 193–207.
Dong, R., Fisman, R., Wang, Y., Xu, N., 2019. Air pollution, affect, and forecasting bias: evidence from Chinese financial analysts. J. Financ. Econ. https://doi.org/10.1016/j.jfineco.2019.12.004.
Easton, D., 1965. A System Analysis of Political Life. John Wiley, New York.
Eaton, S., Kostka, G., 2014. Authoritarian environmentalism undermined? Local leaders' time horizons and environmental policy implementation in China. China Q. 218, 359–380.
Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., Zhou, M., 2015. Growth, pollution, and life expectancy: China from 1991-2012. Am. Econ. Rev. 105 (5), 226–231.
Ebenstein, A., Lavy, V., Roth, S., 2016. The long-run economic consequences of high-stakes examinations: evidence from transitory variation in pollution. Am. Econ. J. Appl. Econ. 8 (4), 36–65.
Fan, M., He, G., Zhou, M., 2020. The winter choke: coal-Fired heating, air pollution, and mortality in China. J. Health Econ. 71 https://doi.org/10.1016/j.jhealeco.2020.102316.
Fowlie, M., Rubin, E., Walker, R., 2019. Bringing satellite-based air quality estimates down to earth. AEA Pap. Proc.. 109, 283–288.
Freeman, R., Liang, W., Song, R., Timmins, C., 2019. Willingness to pay for clean air in China. J. Environ. Econ. Manag. 94, 188–216.
Fu, S., Viard, V.B., Zhang, P., 2021. Air pollution and manufacturing firm productivity: nationwide estimates for China. Econ. J. https://doi.org/10.1093/ej/ueab033.
Ghanem, D., Zhang, J., 2014. Effortless perfection: do Chinese cities manipulate air pollution data? J. Environ. Econ. Manag. 68 (2), 203–225.
Godzinski, A., Castillo, M.S., 2021. Disentangling the effects of air pollutants with many instruments. J. Environ. Econ. Manag., 102489 https://doi.org/10.1016/j.jeem.2021.102489.
Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. Am. Econ. Rev. 102 (7), 3652–3673.
Graff Zivin, J., Liu, T., Song, Y., Tang, Q., Zhang, P., 2020. The unintended impacts of agricultural fires: human capital in China. J. Dev. Econ., 102560 https://doi.org/10.1016/j.jdeveco.2020.102560.
Greenstone, M., Hanna, R., 2014. Environmental regulations, air and water Pollution, and infant mortality in India. Am. Econ. Rev. 104 (10), 3038–3072.
Greenstone, M., He, G., Jia, R., Liu, T., 2022. Can technology solve the principal-agent problem? Evidence from China's war on air pollution. Am. Econ. Rev.: Insights 4 (1), 54–70.
Guo, G., 2009. China's local political budget cycles. Am. J. Polit. Sci. 53 (3), 621–632.
Hanna, R., Oliva, P., 2015. The effect of pollution on labor supply: evidence from a natural experiment in Mexico City. J. Publ. Econ. 122, 68–79.
He, G., Wang, S., Zhang, B., 2020a. Watering down environmental regulation in China. Q. J. Econ. https://doi.org/10.1093/qje/qjaa024.
He, G., Xie, Y., Zhang, B., 2020b. Expressways, GDP, and the environment: the case of China. J. Dev. Econ. 145 https://doi.org/10.1016/j.jdeveco.2020.102485.
He, G., Liu, T., Zhou, M., 2020c. Straw burning, PM2.5, and death: evidence from China. J. Dev. Econ. 145 https://doi.org/10.1016/j.jdeveco.2020.102468.
He, J., Liu, H., Salvo, A., 2019. Severe air pollution and labor productivity: evidence from industrial towns in China. Am. Econ. J. Appl. Econ. 11 (1), 173–201.
Herrnstadt, E., Heyes, A., Muehlegger, E., Saberian, S., 2021. Air pollution and criminal activity: microgeographic evidence from Chicago. Am. Econ. J. Appl. Econ. 13 (4), 70–100.
Heyes, A., Zhu, M., 2019. Air pollution as a cause of sleeplessness: social media evidence from a panel of Chinese cities. J. Environ. Econ. Manag. 98 https://doi.org/10.1016/j.jeem.2019.07.002.
Ito, K., Zhang, S., 2020. Willingness to pay for clean air: evidence from air purifier markets in China. J. Polit. Econ. 128 (5), 1627–1672.
Jia, R., Kudamatsu, M., Seim, D., 2015. Political selection in China: the complementary roles of connections and performance. J. Eur. Econ. Assoc. 13 (4), 631–668.
Jiang, J., Yang, D.L., 2016. Lying or believing? Measuring preference falsification from a political purge in China. Comp. Polit. Stud. 49 (5), 600–634.
Jiang, J., 2018. Making bureaucracy work: patronage networks, performance incentives, and economic development in China. Am. J. Polit. Sci. 62 (4), 982–999.
Jones, B.A., 2020. After the dust settles: the infant health impacts of dust storms. J. Assoc. Environ. Resour. Econ. 7 (6), 1005–1032.
Kahn, M.E., Li, P., Zhao, D., 2015. Water pollution progress at borders: the role of changes in China's political promotion incentives. Am. Econ. J. Econ. Pol. 7 (4), 223–242.
Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. J. Econom. 133 (1), 97–126.
Knittel, C.R., Miller, D.L., Sanders, N.J., 2016. Caution, drivers! Children present: traffic, pollution, and infant health. Rev. Econ. Stat. 98 (2), 350–366.
Kurata, M., Takahashi, K., Hibiki, A., 2020. Gender differences in associations of household and ambient air pollution with child health: evidence from household and satellite-based data in Bangladesh. World Dev. 128, 104779 https://doi.org/10.1016/j.worlddev.2019.104779.
Liu, H., Salvo, A., 2018. Severe air pollution and child absences when schools and parents respond. J. Environ. Econ. Manag. 92, 300–330.
Ma, X., 2019. Consent to Contend: the power of the masses in China's local elite bargain. China Rev. 19 (1), 1–30.
Malmendier, U., Nagel, S., 2011. Depression babies: do macroeconomic experiences affect risk taking? Q. J. Econ. 126 (1), 373–416.
Miller, S., Johnson, N., Wherry, L.R., 2021. Medicaid and mortality: new evidence from linked survey and administrative data. Q. J. Econ. 136 (3), 1783–1829.
Ministry of Ecology and Environment of the People's Republic of China, 2020. Urban Monthly Air Quality Report (In Chinese). Retrieved from. http://www.mee.gov.cn/hjzl/dqhj/cskqzlzkyb/.
Nathan, A.J., 2020. The puzzle of authoritarian legitimacy. J. Democr. 31 (1), 158–168.
Nunn, N., Wantchekon, L., 2011. The slave trade and the origins of mistrust in Africa. Am. Econ. Rev. 101 (7), 3221–3252.
Pargal, S., Wheeler, D., 1996. Informal regulation of industrial pollution in developing countries: evidence from Indonesia. J. Polit. Econ. 104 (6), 1314–1327.
Patel, S., 2015. In: The Dirtiest Cities, Air Pollution Forces Life Changes. Wall Street Journal. https://www.nytimes.com/2015/12/23/world/asia/air-pollution-china-india.html. December 22.
Pew Research Center, 2016. Chinese Public Sees More Powerful Role in World, Names U.S. As Top Threat. Pew Research Center. Retrieved from. https://assets.pewresearch.org/wp-content/uploads/sites/2/2016/10/Pew-Research-Center-China-Report-FINAL-October-5-2016.pdf.
Putnam, D.R., 1993. The Prosperous community. Am. Prospect 4 (13).
Putnam, D.R., 2001. Bowling Alone: the Collapse and Revival of American Community. Simon & Schuster, New York.
Qin, Y., Wu, J., Yan, J., 2019. Negotiating housing deal on a polluted day: consequences and possible explanations. J. Environ. Econ. Manag. 94, 161–187.
Ratigan, K., Rabin, L., 2020. Re-Evaluating political trust: the impact of survey nonresponse in rural China. China Q. 243, 823–838.
Routledge, B.R., von Amsberg, J., 2003. Social capital and growth. J. Monetary Econ. 50 (1), 167–193.
Sager, L., 2019. Estimating the effect of air pollution on road safety using atmospheric temperature inversions. J. Environ. Econ. Manag. 98 https://doi.org/10.1016/j.jeem.2019.102250.
Shen, X., Truex, R., 2021. In search of self-censorship. Br. J. Polit. Sci. 51 (4), 1672–1684.
State Council, 2018. Three-year Action Plan for Cleaner Air Released. State Council, The People's Republic of China. Retrieved from. http://english.www.gov.cn/policies/latest_releases/2018/07/03/content_281476207708632.htm.

Stock, J., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews, Donald W.K., Stock, James H. (Eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge, pp. 80–108 (chapter 5).

Tu, M., Zhang, B., Xu, J., Lu, F., 2020. Mass media, information and demand for environmental quality: evidence from the "Under the Dome". J. Dev. Econ. 143, 102402 https://doi.org/10.1016/j.jdeveco.2019.102402.

van Donkelaar, A., Martin, R.V., Li, C., Burnett, R.T., 2019. Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors. Environ. Sci. Technol. 53 (5), 2595–2611.

Velentgas, P., Dreyer, N.A., Nourjah, P., Smith, S.R., Torchia, M.M. (Eds.), 2013. Developing a Protocol for Observational Comparative Effectiveness Research: A User's Guide. Agency for Healthcare Research and Quality, Rockville, MD. AHRQ Publication No. 12(13)-EHC099.

Wagstaff, A., Lindelow, M., 2008. Can insurance increase financial risk? The curious case of health insurance in China. J. Health Econ. 27 (4), 990–1005.

Waldmeir, P., 2013. March 1st). China Pollution: Fears over Poor Air Exacerbate Healthcare Concerns. Financial Times. https://www.ft.com/content/92fdfb3e-6488-11e2-934b-00144feab49a.

Wang, A., 2013. The search for sustainable legitimacy: environmental law and bureaucracy in China. Harv. Environ. Law Rev. 37, 365–440.

WHO, 2018. Ambient (Outdoor) Air Pollution World Health Organization Newsroom retrieved from. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

Wu, M., Cao, X., 2021. Greening the career incentive structure for local officials in China: does less pollution increase the chances of promotion for Chinese local leaders? J. Environ. Econ. Manag. 107, 102440 https://doi.org/10.1016/j.jeem.2021.102440.

Xu, W., Hou, L., 2014. February 24). People Shun Outdoors amid Smog. *China Daily*. https://usa.chinadaily.com.cn/2014-02/24/content_17300028.htm.

Yang, J., Zhang, B., 2018. Air pollution and healthcare expenditure: implication for the benefit of air pollution control in China. Environ. Int. 120, 443–455.

Zhang, X., Zhang, X., Chen, X., 2017. Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manag. 85, 81–94.

Zhang, J., Mu, Q., 2018. Air pollution and defensive expenditures: evidence from particulate-filtering facemasks. J. Environ. Econ. Manag. 92, 517–536.

Zhang, X., Chen, X., Zhang, X., 2018. The impact of exposure to air pollution on cognitive performance. Proc. Natl. Acad. Sci. USA 115 (37), 9193–9197.

Zhang, Q., Zheng, Y., Tong, D., Shao, M., Wang, S., Zhang, Y., Hao, J., 2019. Drivers of improved PM2.5 air quality in China from 2013 to 2017. Proc. Natl. Acad. Sci. USA 116 (49), 24463–24469.