Greening the Career Incentive Structure for Local Officials in China: Does Less Pollution Increase the Chances of Promotion for Chinese Local Leaders?

Mingqin Wu
School of Economics and Management
South China Normal University, Guangzhou, China

Xun Cao
Department of Political Science
Penn State University

August 17, 2020

Abstract: Does it pay to be "greener" as a local official in China? In this paper, we examine the effect of local environment regulation outcomes, i.e., local pollution, on leaders' chances of promotion. This is an important question because only when the Chinese cadre evaluation system rewards local officials' green behaviors, these officials would move away from their past priority in promoting economic growth at all costs, so that the environmental crisis in China might be addressed. We collect party secretary data for Chinese counties between 2001 and 2014 to measure promotion patterns. We construct county-year SO2 and PM2.5 pollution measures using NASA satellite data. We adopt an instrumental variable approach to deal with potential endogeneity issues of the pollution variables: for PM 2.5, we use a difference-in-differences based instrument, exploring differential effects of provincial pollution reduction targets before and after such targets were imposed; for SO2, we use ventilation coefficient, i.e., the product of wind speed and mixing layer height. Our empirical analysis shows that for county party secretaries, those who were able to reduce air pollution are more likely to be promoted. We find similar results for county magistrates. However, we do not find evidence for the pollution-promotion link for prefecture and provincial party secretaries.

Acknowledgement: An earlier version of this paper was presented at the 5th Environmental Politics and Governance (EPG) Conference, Santa Barbara, CA, June 27-29, 2019. We received valuable comments from participants of the conference. All errors are ours. For questions and suggestions, please email Xun Cao (xuc11@psu.edu).

1. Introduction

The emerging environmental crisis in China has attracted much attention from practitioners and academics (Economy 2004; Shapiro 2012). Environmental challenges pose considerable threats to China's long-term development (Tilt 2013). In addition to the detrimental effects on its own environment, Chinese environmental crisis has profound global implications. For instance, with its increasing economic size and energy consumption, China is now the largest emitter of carbon dioxide in the world. In 2018, Chinese emissions of roughly 13.5 Gt CO_2 were approximately 25% of the global total (Olivier and Peters 2018).

The environmental crisis in China is not only a natural outcome of economic growth in a typical developing country going through industrialization. Rather, there are deep political reasons, one of which has to do with the incentive structure for local officials who have long been prioritizing economic development at the expense of the environment. Chinese cadre evaluation system promotes those who deliver high priority targets. Local leaders are motivated to develop local economy because upper-level governments make promotion decisions by evaluating the relative economic growth of jurisdictions (Maskin et al. 2000). To generate better economic growth, local governments often sacrifice the environment by, for instance, lessening or non-compliance with existing regulations to lower local firms' production costs.

The public and the central government have become acutely aware of such a built-in "environmentally unfriendly" incentive in the cadre evaluation system. The central government has implemented various policies to address severe environmental issues. For instance, in 2013, the State Council approved the *Action Plan for Air Pollution Prevention and Control*, which outlines specific PM2.5 air pollution targets for local governments. In recent years, new targets including environmental protection have been added as high priority targets for local officials. The central government expects that such changes would incentivize local officials to reduce pollution.[1] However, for many scholars, when it comes to performance evaluation, promoting economic growth is still considered by most local officials as the safest bet for career advancement (Li and Zhou 2005; Heberer and Senz 2011).

This paper tests whether local officials' green efforts, reflected by better local environmental outcomes, are rewarded by the cadre evaluation system since the early 2000s. This is an important question, because only when the system rewards green behaviors, local officials might move away from their past priority in promoting economic growth, so that the environmental crisis in China might be addressed. We first collect county party secretary data for over 2000 Chinese counties between 2001 and 2014 to measure their promotion patterns. We construct county-year level SO_2 and PM2.5 air pollution measures, using fine-grained NASA satellite data. We adopt an instrumental variable approach to deal with potential endogeneity issues of the pollution variables: for PM 2.5, we use a difference-in-differences based instrument, exploring differential effects of provincial pollution reduction targets on pollution, before and after such targets were imposed; for SO_2, we use ventilation coefficient,

[1] Yin et al. (2019) consider integrating environmental performance into the cadre evaluation system one of the two future mechanisms to strengthen traditional command and control regulations; the other involves leveraging the power of financial sectors.

i.e., the product of wind speed and mixing layer height. Our empirical analysis shows that for county party secretaries, those who were able to reduce air pollution were much more likely to be promoted. We extend our analysis to county magistrates and find similar results. However, when we further extend our study to prefecture and provincial party secretaries, we do not find any evidence for the pollution-promotion link.

We are not the first to empirically test the connection between pollution and cadre promotion in the Chinese context. A few recent studies have started to tackle this pollution-promotion question. Using data on energy intensity, air pollution treatment spending, and air pollution from 86 major Chinese cities, Zheng et al. (2014) find that better environmental performances are associated with a higher chance of city mayor promotion.[2] Chen et al. (2016) show a positive connection between energy productivity and provincial governors' promotion in 31 provinces. Using data from 100 Chinese cities, Pu and Fu (2018) show that pollution decreases the chances of promotion for city mayors, with the effect varying cross regions and by pollutants. Feng et al. (2018), however, find that environmental performance does not significantly impact political turnovers of municipal party secretaries during 2002-2013. Most recently, Wang and Lei (2020) show that local officials' efforts towards environmental protection contribute to their political promotion for a panel of all prefecture-level party secretaries and governors during 1996-2013.

How is our paper different? Firstly, unlike past studies that either use data from the provincial level or from Chinese prefectural cities, we extend this empirical literature to a lower administrative level. This county-level focus has several advantages. For instance, county-level pollution data is much more fine-grained. In China, even prefectures are often very large: e.g., the Daxing'anling Prefecture (46,755 km^2) in Heilongjiang, not even a top 20 prefecture by size, is roughly the size of Estonia and is larger than Denmark. There is often significant within-prefecture variation in air pollution. Using prefecture or province pollution averages often washes out pollution hotspots in the data. Moreover, counties are historically the most basic units of administration reached by the central government in China.[3] Most day-to-day functions of the government, including environmental protection, ultimately are being implemented by county governments. The county-level bureau of environmental protection is the last layer of the environmental protection branch of the government: there is no office or bureau below the county level. Indeed, the importance of the county economy has become even more pronounced after the tax reform in 1994. After this reform, local governments' economic growth strategy changed from industrialization based on corporate profits to urbanization based on land finance (Kung et al. 2013). County governments have been granted land transfer rights so that they can promote economic growth through low-cost land transfers for investment, real estate development, and establishing financing platforms for infrastructure construction. More recently, county governments have been continuously given greater importance, a trend that is embodied in a series of reforms such as an

---

[2] Though the statistical significance level of such an association varies by model specification and energy/pollution indicators used.

[3] Historically, the Chinese central government could not research below the county level of administration. At levels below county (i.e., townships and villages), public goods and other government functions were historically delegated to local elites.

“expansion of power to create strong counties” (Kuo Quan Qiang Xian) and “provincial directly managed counties” (Sheng Zhi Guan Xian).

Secondly, we use the same instrumental variable strategy to explain promotion of county magistrates and prefecture and provincial party secretaries. We find a similar causal effect of pollution on promotion for county magistrates. But there is no evidence for the pollution-promotion link at the prefecture and provincial levels. This is a significant contribution as it reveals that for party secretaries – those who are in real charge at every level of the government, the causal effect of pollution on promotion only works at the county level. More importantly, this empirical finding provides an important insight into how the Chinese central government strategically shifts the relative importance between competence and loyalty in cadre promotion as a function of cadre ranks. Analyzing promotion of provincial, prefectural, and county party secretaries and government executives between 1999 and 2007, Landry et al. (2018) also only find evidence for performance-based promotion at the county level. Their performance measure is economic growth, ours is based on pollution, both reflecting local leaders’ competence, which is often contrasted with loyalty as two competing forces for promotion. Why the performance-based promotion only works at the county level? We share a similar explanation as in Landry et al. (2018): local officials who are distant in hierarchy from central rulers have no direct influence on central leader selection, therefore posing little threat even if they are not loyal; they are therefore evaluated based on competence as central leaders need to incentivize them for economic growth and pollution reduction. Higher ranked officials, on the other hand, are within the selectorate that is key to the survival of the central rulers: their loyalty matters much more than competence.

Thirdly, unlike past studies that test statistical associations between pollution and promotion, we adopt an instrumental variable estimation that enables us to make a causal claim. For PM2.5, following recent studies such as Lu et al. (2017), we use a difference-in-differences based instrument, i.e., the interaction between provincial pollution reduction targets of the 11^{th} Five-year Plan (2006-2010) and a post-2005 dummy variable. For SO2, we use ventilation coefficient. This is the product of wind speed and mixing layer height, with the former determining horizontal dispersion of pollution while the latter the height within which pollutants disperse. The higher the wind speed and the mixing height, the faster the dispersion of pollutants, therefore the lower the level of air pollution (Arya 1998). Our instrumental variable approach also helps to address a reverse causality concern that high promotability leaders were assigned to jurisdictions with a better potential in pollution reduction. For instance, local ventilation coefficients often exhibit significant year-by-year changes. Such temporal changes are a function of meteorological conditions that are difficult to predict for the medium and long terms. It is very unlikely that leaders can self-select in and out of counties depending on (poorly predicted) expected year-to-year changes in local ventilation coefficients.

Finally, our paper makes general contributions to the literature on environmental outcomes in developing countries and to the literature on the political foundations of pollution. One of the most fundamental questions for environmental and developmental economics is to explain environmental outcomes in developing countries, i.e., “why environmental quality is so poor in developing countries?"[4] Greenstone and Jack (2015) synthesize four potential explanations: low marginal willingness to pay for environmental goods, high marginal costs of investments in environmental quality improvements, political economy of rent-seeking behaviors, and market failures (e.g., under-provisions of public goods and negative externalities) and imperfections (e.g., missing land, capital, and labor markets). Our paper speaks directly to the third explanation which often focuses on the role of incentive structure. Firms respond to the incentive structure set up by regulators (McRae 2015). So do government officials. Recent studies present new evidence that improving incentives can improve monitoring and enforcement outcomes. For instance, experimental evidence from Duflo et al. (2013) shows that altering market structure incentivized accurate reporting by third-party auditors in India. In Kahn et al. (2015), interjurisdictional water pollution was reduced significantly in China after a new local cadre promotion rule was established to reward pollution reductions along administrative boundaries. Our paper contributes to this emergent literature at the intersection of developmental and environmental economics by focusing on one of the most important incentive structure changes – a shift away from a growth-at-all-cost incentive structure to one that emphasizes environmental protection – in the largest developing in the world, China.

In addition, there is a literature in economics and political science that study the political foundations of pollution. The focus here is whether and how political regime types affect environmental performances. The literature often contrasts democracies with autocracies. Overwhelming theoretical propositions favor the former as the better system. For instance, democracy is said to be associated with more citizen influence on policies through the ballot box, pressure groups, and a free media (Payne 1995). However, no clear pattern has emerged from the empirical studies (Grafton and Knowles 2004; Binder and Neumayer 2005; Fredriksson et al. 2005; Bernauer and Kuobi 2009). Such mixed empirical findings have motivated the field to move beyond a simple democracy-autocracy dichotomy and to focus on detailed causal mechanisms connecting political dynamics to environmental outcomes. For instance, recent studies examined variations within democracies regarding institutional differences such as proportional vs. majoritarian electoral rules and presidentialism vs. parliamentarianism (Fredriksson and Millimet 2004; Fredriksson and Wollscheid 2007). Our paper contributes to this much more nuanced view of political regimes' environmental impacts. We show that even in the absence of electoral competition, an incentive structure that rewards better environmental performances can be established so that local officials who are able to reduce pollution are more likely to be promoted. This top-down approach serves as a substitutive institution to reward green local leaders, therefore increasing environmental quality in countries without an established democratic rule.

2. Literature and Theoretical Expectations

The alarming level of environmental degradation in China is not simply a natural outcome of economic growth and industrialization in a typical developing country. Rather, there are deep political reasons, one of which has to do with the incentive structure for local officials who,

[4] See also a special issue on this topic in the *Journal of Environmental Economics and Management*: e.g., Jack (2017) for the introduction.

many believe, have long been prioritizing economic development at the expense of the environment (Economy 2004; Shapiro 2012).

Career Incentive Structure and its Environmental Implications

Chinese local leaders' behaviors are driven by a cadre evaluation system in which those who deliver high priority targets are more likely to be promoted. This political tournament theory posits that local cadres engage in a tournament-style competition with their peers in neighboring jurisdictions over promotions to the next level (Chen et al. 2005; Li and Zhou 2005; Wu and Chen 2016). To maximize the chances of promotion, they are motivated to develop local economies because the upper-level government makes promotion decisions by evaluating their performances based on the relative economic growth of jurisdictions (Maskin et al. 2000).

This political tournament theory has received criticisms. For instance, the economic performance of local leaders itself can be endogenous: officials with close ties to central leaders are more likely to be assigned to places with better growth potential (Opper and Brehm 2007). As a result, many argue that factors such as loyalty or faction decide promotion (Shih, Adolph and Liu 2012.).[5] Despite the aforementioned criticism, this career incentive approach has been broadly applied in recent studies of Chinese politics and economics, including topics such as leaders and factions within the Chinese Communist Party (Shih, Shan, and Liu 2010), the effects of faction ties and competence on promotion (Choi 2012), judicial cadre evaluation and court leader performances (Kinkel and Hurst 2015), local cadres' responses to changes in target-based cadre evaluation system (Gao 2015), and the changing priorities of local leaders from economic development to social welfare (Zuo 2015).

What are the environmental implications of such a career incentive structure? To generate better economic growth, local governments often sacrifice the environment. In the Chinese context, many environmental laws and regulations are designed at the central level. Their implementation, on the other hand, is largely in the hands of local leaders. It is the implementation of existing laws and regulations that can be manipulated by local officials. Lessening implementation or non-compliance lowers firms' production costs. Dasgupta et al. (2001) show that for a small paper factory in China that on average discharges 327,800 tons of wastewater yearly, the cost of reducing 90% suspended solids alone is $452,364 in 1994. Moreover, if firms are mobile, jurisdictions with lower de facto environmental regulations attract pollution intensive firms. This is the pollution haven hypothesis, which has received empirical support in the Chinese context (Dean et al. 2009). For instance, Zhu et al. (2014) find that Chinese pollution-intensive firms have relocated from the coastal province Zhejiang to inland China, where enforcement of environmental regulation is laxer.

Indeed, legal scholars have pointed out that the Chinese national environmental legislation on paper is plentiful and powerful; the problem is local enforcement. For instance, despite central government's efforts to clean up, the Huai River remains one of the most polluted in China, because polluting factories along the river contribute significantly to local economy. Local officials had strong incentives not to (fully) enforce environmental regulations (Economy 2004). More recently, Cai et al. (2016) show that local governments

[5] Jia et al. (2013) find that connection and performance are complements in promotion.

can affect the stringency of enforcement via the collection of pollution fees and the inspection of violations. Cao et al. (2019) show that Chinese prefecture leaders' selective enforcement of environmental regulations creates an environmental political business cycle in which pollution increases in years leading to the year of leader turnover.

Unprecedented Environmental Crisis and A Changed Incentive Structure?

The public and the central government have become acutely aware of such a built-in "environmentally unfriendly" incentive in the traditional cadre evaluation system. Indeed, the central government has implemented various policy schemes to address severe environmental issues. Recent studies focus on the effectiveness of such policy initiatives (Kahn et al. 2015; Chen et al. 2018). For instance, since 1996, the central government has identified "three rivers and three lakes basins" (3Rs3Ls) as key regions for water pollution control. Wang et al. (2018) evaluate the effects of the water quality regulations in the 3Rs3Ls basins. They find that such regulations forced out small, heavily polluting firms, but had no effect on surviving firms' productivity. In 1998, a Two Control Zones (TCZ) policy was implemented by the central government in which tougher environmental regulations were imposed in TCZ cities. Cai et al. (2016) find that environmental regulations in the TCZ cities indeed affects patterns of foreign direct investment, especially for those from countries with better environmental protections. In 2006, the 11^{th} Five-year Plan from the central government assigned different pollution reduction quota to provincial governments. Shi and Xu (2018) reveal a heterogenous effect of cross-province variations in policy intensity (in reducing pollution) on the content and volume of Chinese firm exports: interestingly, state-owned enterprises (SOEs) and firms in the central and western part of China are much less affected.

Other policy instruments have also been applied by the government. Zhang et al. (2018) study the National Specially Monitored Firms (NSMF) program in which central supervision is applied to firms that are listed as NSMF. They find that central supervision significantly reduces industrial COD emissions by at least 26.8%. Focusing on another policy innovation – government environmental interviews with firms (Huan Bo Yue Tan), Shen and Zhou (2017) find that the environmental performances of companies in the interviewed areas have improved significantly. Karplus and Wu (2019) and van der Kamp (2018) study the effect of central government top-down inspection campaigns. The former shows that such crackdowns result in a large reduction in SO2 emissions in short periods before pollution reverts to prior levels after crackdowns end. The latter finds that such a police patrol instrument does not even have a significant short-term effect.

In recent years, environmental protection has been added as a high priority target for local officials' evaluation. The motivation is that such changes would incentivize local officials to be "green." However, many scholars still believe that when it comes to maximize the chances of promotion, economic growth is still considered the safest bet for most local officials (Li and Zhou 2005; Heberer and Senz 2011). Whether local officials in China would respond to this "greener" incentive structure largely depends on whether their green efforts, as reflected by better local environmental outcomes, would be rewarded by the cadre evaluation system. This is the focus of our study, that is, all else equal, *does less local pollution increase the chances of promotion for Chinese local leaders?*

3. Data

Measuring Local Officials' Promotion

In this paper, we examine the effect of local environment regulation outcomes – local pollution – on local leaders' chances of promotion to a higher-level post. China has 334 prefecture-level administrative units that are further divided into 2,862 county-level units. We first focus on county party secretaries because they are higher in rank than county magistrates and are the primary decision-makers when it comes to salient policies.[6] The dependent variable, *political turnover*, is binary and is defined as follows:

$$political\ turnover = \begin{cases} 1: promoted\ \begin{pmatrix} move\ from\ county\ to\ district; from\ county\ and \\ district\ to\ higher\ position\ at\ prefecture\ and\ above \end{pmatrix}; \\ 0: same\ job\ or\ job\ move\ at\ the\ same\ level; \end{cases}$$

This binary "promotion" variable equals to 1 if an official gets a promotion; 0 if moving between different counties or staying at the same level of departments. Demoted, retired, and punished officials are not included. This is because demotion, punishment, and retirement reflect special circumstances that often have little to do with a cadre's economic and environmental performances. For instance, a cadre is retired due to his/her age; he/she is punished for his/her crime. To construct this *political turnover* variable, we obtain county party secretary names from province yearbooks and search biographies from Baidu Encyclopedia to get information regarding age, gender, education, place of birth, and working experiences. All years are included in the sample, not just the years with a turnover event. In the online appendix, we include robustness checks that use a *political turnover* variable that treats demotion, retirement, and punishment also as 0. We obtain similar results using this alternative measure of promotion outcome (Table A2-A3).

Later in this paper, we extend our analysis to county magistrates and prefecture and provincial party secretaries. We define the political turnover variable for a county magistrate as 1 if he/she is promoted to be a county party secretary or any position that would be considered a promotion for county party secretaries (i.e., a move from county to district; from county and district to higher position at prefecture and above); and 0 otherwise. Similarly, county magistrates who are retried, demoted, or punished are not included in the analysis presented in the main text. In the online appendix (Table A4-A5), we present results (which are similar) using the alternative promotion outcome variable that treats demotion, punishment, and retirement also as 0. At the prefecture level, we define a prefecture party secretary as promoted if he/she is promoted to key positions at the province level or above (Jiang 2018). At the province level, we define a province party secretary as promoted if he/she is promoted to be a member of the Politburo, a standing member of the Politburo, the premier of state council, a vice premier of state council, or a member of the state council.

[6] Eaton and Kostka (2014), for instance, argue that "Within the leadership group, party secretaries usually hold the pre-eminent position and are seen as the first hand."

Measuring Local Air Pollution

Our empirical analysis uses satellite data from the National Aeronautics and Space Administration (NASA). We use two types of air pollutant data: PM2.5 and SO2.[7] The PM2.5 data have been used in recent articles such as Cao, Kostka, and Xu (2019). These are annual average concentration data, covering 1998-2016, and are provided in grid-cells with 0.1 × 0.1 decimal degree resolution (about 11km by 11km). We re-sampled the grid data in ArcMap so that each grid is evenly divided into 100 smaller grids. We calculated the county-year annual average concentration levels by overlaying the resampled PM2.5 grids over Chinese county polygons and taking the average PM2.5 annual concentration levels of all grids falling within a county polygon.

The SO2 data are much more recent. They are provided by 0.125 x 0.125 decimal degree global grids, about 13km by 13km at the equator. One complication is that these are daily data from 2005 to 2018.[8] We processed all data between 2005 and 2018, took annual averages based on daily data, re-sampled the data so that each grid is evenly divided into 100 smaller grids, and we overlaid them to polygons of Chinese counties: the end results are annual averages of SO2 concentration levels at the county level. Figure 1 shows county annual averages of SO2 concentration for 2005 and 2015: note that 2005 is the last year before the 11th Five-year Plan which added environmental performances into the cadre evaluation system. It seems that China has significantly reduced its SO2 air pollution since 2005.

PM2.5 and SO2 are highly correlated in our data. The correlations are higher than 0.6 when looking at the data yearly. Indeed, SO2 is a precursor to PM2.5 formation, which makes PM2.5 a good proxy for SO2. There are a few advantages to use both air pollutants. PM2.5 data has a much longer temporal coverage (starting 1998), which turns out to be necessary for our difference-in-differences based instrumental variable approach that requires pre-treatment periods, i.e., years before the 11th Five-year Plan (2006-2010). However, PM2.5 often can travel over long distances. SO2 is much less subject to this concern, therefore often considered a better indicator of local air pollution.

There are a few reasons for our choice of satellite air pollution data. First, there is no systematic official air pollution data at the county level in China. Even at the prefecture-city level, official air pollution data from monitoring stations is only available for very recent years.[9] In the absence of official county level data, satellite data have been used in many

---

[7] PM2.5 data is from: http://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod. SO2 is from OMI/Aura Sulphur Dioxide (SO2) Global Gridded V3: https://disc.gsfc.nasa.gov/datasets/OMSO2G_V003/summary?keywords=so2. Both last accessed in January 2019.

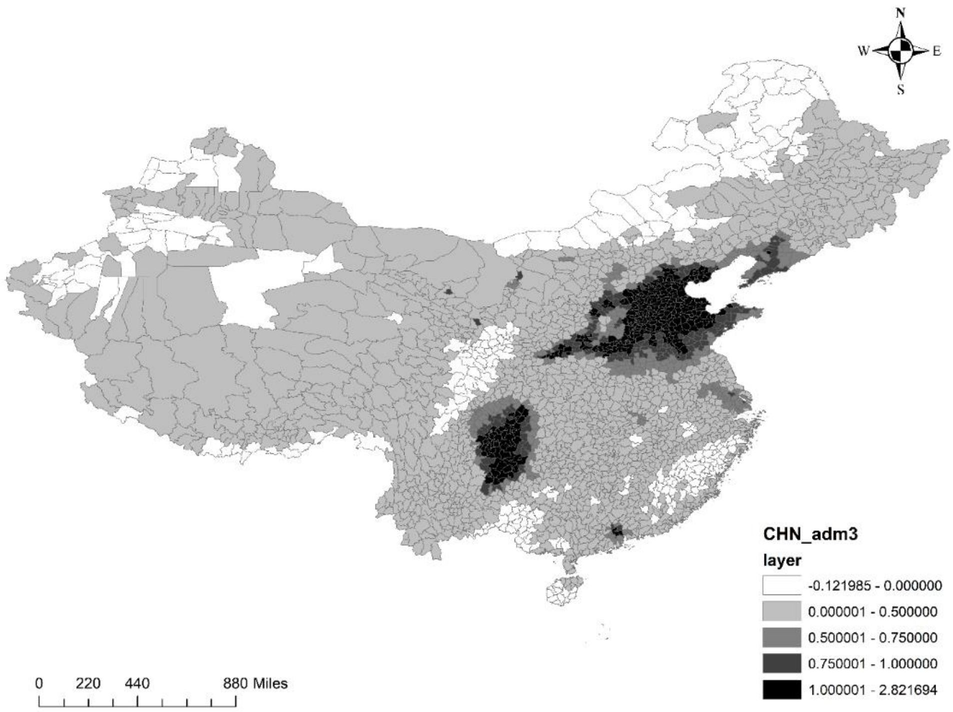
[8] Daily data for 2004 are available but do not cover all days for most of the grids. Therefore, we do not use data from 2004.

[9] According to Freeman et al. (2019): "Existing studies of air pollution in China typically use the Air Pollution Index (API) and PM10 data from the Ministry of Environmental Protection of China. However, API and PM10 data can only be obtained in large and medium-sized cities in China, and PM2.5 data were not published until 2014." The Chinese City Statistical

studies as a good measure for local air pollution (Li et al. 2011; Streets et al. 2013). Second, we checked the correlations between satellite and monitor station data for prefecture/cities.[10] The correlation between monitoring station SO2 data and the satellite SO2 data used in this study, for prefecture cities and years covered by both data sources (326 prefecture cities and for 2014-2017), is 0.714. We conducted the same exercise for PM2.5: the correlation is 0.681. Both correlations are very high, indicating that satellite data is indeed a very good proxy for government monitoring station data.

Finally, one might question whether the use of satellite data is appropriate when a county leader's superiors only have official pollution data that can suffer from data manipulation. Chen et al. (2012) and Ghanem and Zhang (2014) suggest that data manipulation happens often in the form of local governments changing pollution statistics downward from above to below the warning line to avoid punishment. In our online appendix, we show that with such a downward manipulation in the official pollution data, the use of satellite data would be biased *against* us finding a negative relationship between pollution and a local leader's chances of promotion.[11]

Figure 1: County-level annual averages of SO2 concentration, 2005 and 2015.

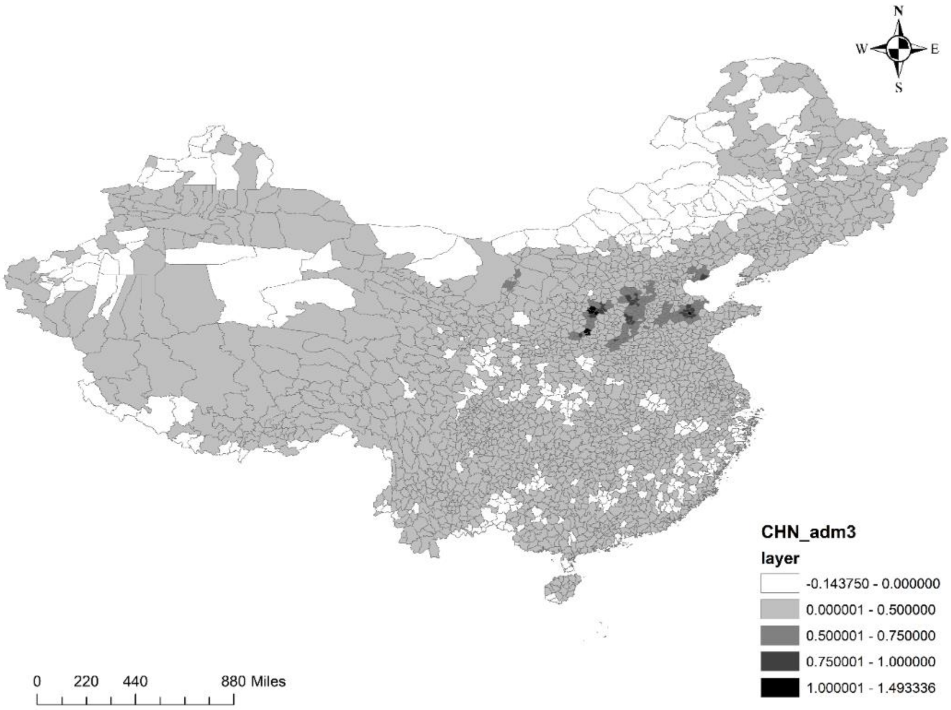


Yearbooks have data on the volume of SO2 exhausted (ton) since 2003 for many prefecture cities: but these are industrial sources of SO2 only.

[10] The only open source monitoring station data that we are aware of is from the Chinese Air Quality Historical Database: https://www.aqistudy.cn/historydata. It provides daily data for air pollutants such as AQI, PM2.5, PM10, SO2, CO, NO2, and O3.

[11] See Section C of the online appendix for more details.

(a): 2005



(b): 2015

Control Variables

We include a battery of county characteristic variables, including per capita GDP, fiscal revenue, total population, infrastructure expenditures, and industry production in each county-year as well as county leader characteristics such as gender, education, age, age square, tenure length, and political connection.[12] The data of county characteristics comes from Provincial Yearbooks and National County (Prefecture) Social Economic Statistical Yearbooks. We also control for PM2.5/SO2 in each prefecture-year in most model specifications and the average PM2.5/SO2 level of the predecessor when we control for the predecessor effect (e.g., Column (2) of Table 4). Table 1 presents the basic summary statistics for variables included in the main analysis: note in our sample, we exclude Beijing, Tianjin, Shanghai, Chongqing because they are municipalities directly under the central government; we also exclude Tibet, Qinghai, and Hainan due to the data availability.

[12] Regarding the political connection variable, for county party secretaries and county magistrates, it is 1 if the county leader was born at the same county or same prefecture with the prefecture governor or prefecture party secretary; and 0 otherwise. For a prefecture party secretary, we define connection as 1 if he/she and his/her provincial party secretary share the same birth province. For a province party secretary, we define connection to be 1 if he/she has working experiences in central government, which allow him/her to maintain a stronger connection with the centre and a better knowledge of the workings of central appointment procedures (Li and Zhou 2005).

Table 1. Summary statistics for the key variables.

Variables	Definition	Mean	S.td.	Obs.
Variables for county party secretary				
Dependent variable:				
Political turnover	Promotion=1, no promotion=0	0.160	0.366	14,175
Independent variables:				
Post	Post=1 if year>=2006, 0 otherwise	0.690	0.463	14,175
Target (log)	The emission reduction target	-2.295	0.697	14,175
VC	Ventilation coefficient (log)	7.339	0.289	10,022
PM 2.5	Moving average PM2.5 during the tenure	0.350	0.167	14,175
SO2	Moving average So2 during the tenure	0.480	0.468	10,022
Control variables				
Gender	Female=0, male=1	0.968	0.176	14,175
Education	Associate degree or below=0; Bachelor's degree or above=1	0.950	0.219	14,175
Age	Age of official in each year	46.804	3.862	14,175
Tenure	The number of years spent at current tenure	4.212	1.727	14,175
Connection	=1 if the leader was born in the same county or prefecture with prefecture leaders, 0 otherwise	0.136	0.343	14,175
PPM2.5	The average PM2.5 of the predecessor's tenure	0.341	0.162	14,175
APM2.5	The mean PM2.5 in each city-year	0.356	0.366	14,175
clnRGDP	GDP per capita in each county-year, yuan (log)	9.473	0.924	14,175
clnFisrev	Fiscal revenue in each county-year, 10000 yuan (log)	10.044	1.368	14,175
clnPop	Population in each county-year, 10000 persons (log)	3.748	0.736	14,175
clnInfraexp	Infrastructure expenditures in each county-year, 10000 yuan (log)	12.084	1.714	14,175
clnIndus	Industry production in each county-year, 10000 yuan (log)	12.317	1.480	14,175
Variables for county magistrate				
Dependent variable:				
Political turnover	Promotion=1, no promotion=0	0.215	0.411	11,146
Variables for prefecture party secretary				
Dependent variable:				
Political turnover	Promotion=1, no promotion=0	0.087	0.281	3,337
Independent variables:				
Post	Post=1 if year>=2006, 0 otherwise	0.658	0.474	3,337
Target (log)	The emission reduction target (log)	-2.281	0.682	3,337
Pref_PM2.5	Moving average PM2.5 during the tenure	0.353	0.156	3,337
Pref_SO2	Moving average So2 during the tenure	0.321	0.391	2,448
Control variables				
Gender	Female=0, male=1	0.967	0.179	3,337
Education	Associate degree or below=0; Bachelor's degree or above=1	0.997	0.055	3,337

Age	Age of official in each year	52.052	3.737	3,337
Tenure	The number of years spent at current tenure	4.353	1.822	3,337
Connection	=1 if the leader was born in the same province with province leaders, 0 otherwise	0.103	0.304	3,337
PrefAPM2.5	the mean PM2.5 in each province-year	0.356	0.139	3,337
PreflnRGDP	GDP per capita in each city-year, yuan (log)	9.775	0.847	3,337
PreflnFisrev	Fiscal revenue in each city -year, 10000 yuan (log)	12.771	1.217	3,337
PreflnPop	Population in each city -year, 10000 persons (log)	5.893	0.613	3,337
PreflnInfraexp	Infrastructure expenditures in each city -year, 10000 yuan (log)	14.976	1.242	3,337
PreflnIndus	Industry production in each city -year, 10000 yuan (log)	15.690	1.421	3,337
Variables for provincial party secretary				
Dependent variable:				
Political turnover	Promotion=1, no promotion=0	0.033	0.180	331
Independent variables:				
Post	Post=1 if year>=2006, 0 otherwise	0.640	0.481	331
Target (log)	The emission reduction target (log)	-2.142	0.806	331
Prov_PM25	Moving average PM2.5 during the tenure	0.314	0.141	331
Prov_SO2	Moving average So2 during the tenure	0.356	0.337	237
Control variables				
Gender	Female=0, male=1	0.991	0.095	331
Education	Associate degree or even below=0, bachelor’s degree or above=1	0.946	0.227	331
Age	Age of official in each year	59.012	4.117	331
Tenure	The number of years spent at current tenure	4.346	2.503	331
Connection	=1 if the leader has central working experiences, 0 otherwise	0.498	0.501	331
ProvlnRGDP	GDP per capita in each province-year, yuan (log)	9.819	0.751	331
ProvlnFisrev	Fiscal revenue in each province-year, 10000 yuan (log)	14.953	0.825	331
ProvlnInfraexp	Infrastructure expenditures in each province-year, 100 million yuan (log)	8.386	1.132	331
ProvlnIndus	Industry production in each province-year, 100 million yuan (log)	9.091	1.261	331

4. Empirical Strategy

To investigate the effect of environmental performance on local officials’ promotion, we use the following benchmark model for PM 2.5:

$$\text{political turnover}_{ict} = \alpha_1 \text{PM2.5}_{ict} + \alpha_2 X'_{ct} + \alpha_3 Z'_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \quad (1)$$

And the benchmark model for SO2 is:

$$\text{political turnover}_{ict} = \beta_1 \text{SO2}_{ict} + \beta_2 X'_{ct} + \beta_3 Z'_{ict} + \eta_c + \theta_t + \epsilon_{ict} \quad (2)$$

Where the dependent variable $\text{political turnover}_{ict}$ is the turnover of local official *i* in county *c* in year *t*. PM2.5_{ict} is the average of PM2.5 during the tenure for local official *i* in county *c* in year *t*, and SO2_{ict} is the average of SO2 during the tenure for local official *i* in county *c* in year *t*. X_{ct} is a vector of time-varying county characteristics, such as per capita GDP, fiscal revenue, total population, infrastructure expenditures, and industry production. Z_{ict} is a vector of time varying characteristics of local officials, such as gender, education, age, age square, tenure length, and connection. η_c is county fixed effect, capturing all time-invariant differences across counties, and θ_t is year fixed effect, capturing all yearly factors that are common to counties such as macro-level shocks. ε_{ict} and ϵ_{ict} are error terms. Following Bertrand, Duflo, and Mullainathan (2004), we address the potential serial correlation and heteroskedasticity issues by clustering the standard errors at the city level.

A key assumption for obtaining an unbiased estimation for α_1 or β_1 is that conditional on all the control variables, the variable of interest, PM2.5_{ict} or SO2_{ict}, is uncorrelated with the error term. However, it is possible that PM2.5_{ict} and SO2_{ict} are endogenous. For instance, cadres with higher probability for promotion are appointed to counties with better potentials in environment protection and economic growth. This reverse causality issue can generate a biased estimation. In addition, omitted variables, such as the ability of local officials, which often cannot be measured directly and accurately, could also cause a biased estimation of key explanatory variables.

To deal with these endogeneity issues, in addition to the benchmark models, we adopt an instrumental variable approach.[13] More specifically, when we use PM2.5 to measure local air pollution, we take advantage of cross-province variations in pollution reduction targets imposed by the 11th Five-year Plan to examine the effect of pollution on local officials' promotion.[14] Intuitively, we compare promotion of local officials in provinces with larger pollution reduction targets with promotion in provinces with smaller pollution reduction targets, before and after the beginning of the 11th Five-year Plan (2006-2010). In other words, in this difference-in-differences based instrumental variable estimation (Lu et al. 2017), we use the interaction term between the provincial pollution reduction target ($Treatment_c$) and a post-2005 dummy variable ($post_t$) as the instrument. The first stage of the instrumental variable estimation for PM 2.5 is:

$$\text{PM2.5}_{ict} = \gamma_1 Treatment_c \times post_t + \gamma_2 X'_{ct} + \gamma_3 \text{Z}'_{ict} + N_c \times f(t) + \eta_c + \theta_t + \vartheta_{ict} \quad (3)$$

$Treatment_c$ is the provincial level pollution reduction target for county c, same for all counties in the same province; $post_t$ is a dummy variable indicating the years during and after the 11th Five-year Plan: it is 0 before 2006; 1 otherwise.

---

[13] In the online appendix, Section D, we present results from an earlier version of this paper in which a difference-in-differences (DID) approach is used instead of the current instrumental variable approach. We decided to present the DID results only in an online appendix is because first, our key explanatory variables (PM2.5 and SO2) might be endogenous. Second, we observe a pre-trend when testing the parallel trend assumption using the full sample. However, we have an explanation on why we observe this pre-trend. Following this explanation, we limit our sample to non-TCZ counties and this pre-trend disappears (Figure D1 of the appendix).

[14] Table B1 of the online appendix provides the reduction targets data.

The pollution reduction target is not determined randomly; the difference in political turnovers between high-targets and low-targets counties could be a function of pre-existing differences. To deal with this issue, following Gentzkow (2006) and Lu et al. (2017), we identify the determinants (N_c) of the pollution targets, and control for the different trends in turnovers by interacting these determinants variables (N_c) with a third-order polynomial function of time, $N_c \times f(t)$. After carefully reading central government's main document explaining the allocation of pollution reduction targets – "National Total Pollutant Emission Control Plan during the 11th Five-Year Plan" – we include target determinants such as provincial environment quality, environment capacity, emission base, economic development, pollution reduction capability, and geographical factors.[15]

SO2 data are only available from 2005 to 2014; we cannot adopt the same difference-in-differences based instrumental variable approach because we only have one year for the pre-treatment period (i.e., 2005). Therefore, we use another instrument: ventilation coefficient, which is the product of wind speed and mixing layer height. Wind speed determines horizontal dispersion of pollution while mixing height determines the height within which pollutants disperse. These two elements are key meteorological determinants for pollution concentration: the higher the wind speed/mixing height, the faster the dispersion of pollutants, the lower the level of local air pollution (Arya 1998). Indeed, we find that counties with higher ventilation coefficients are associated with lower SO2 (the first stage regression, Column (3) of Table 3), confirming the relevance condition of this instrument. Ventilation coefficient is determined by meteorological and geographical conditions, therefore also meeting the exogeneity requirement/exclusion restriction of an instrument.

Since Broner et al. (2012), several studies use ventilation coefficient as an instrument for air pollution and environmental regulation stringency (Hering and Poncet 2014; Cai et al. 2016; Bagayev and Lochard 2017; Shi and Xu 2018; Li et al. 2020). We obtain the wind speed information at the 10-m height and the boundary layer height, which is used to measure mixing height, from the European Center for Medium-Term Weather Forecasting ERA-interim dataset. We match the ERA-interim dataset with the seat of each county by latitude and longitude. Ventilation coefficients are calculated as annual averages for each county, 2005 to 2014. The first stage of the instrumental variable estimation for SO2 is:

$$\mathrm{SO2}_{ict} = \delta_1 \mathrm{VC}_{ct} + \delta_2 X'_{ct} + \delta_3 Z'_{ict} + \eta_c + \theta_t + \mu_{ict} \quad (4)$$

VC_{ct} is the ventilation coefficient for county *c* in year *t*, X_{ct} is the vector of time-varying county characteristics, Z_{ict} is a vector of time varying characteristics of local officials, η_c county fixed effect, and θ_t year fixed effect.

[15] Details of these determinant variables are listed in Table A1 of the online appendix.

5. Empirical Results

Main results using PM2.5

Empirical results regarding the effect of PM 2.5 on county party secretaries' promotion are reported in Table 2. In Column (1), we report findings from an OLS estimation where we do not address potential endogeneity issues for PM 2.5: here we find that PM2.5 is negative associated with promotion; this association is statistically significant.

Results using a difference-in-differences based instrument are in Column (3): Panel B has the first stage result; here, the instrument, $Treatment_c \times post_t$, has a negative and statistically significant effect on PM 2.5, suggesting that a larger pollution reduction target reduces pollution level and therefore proving the relevance condition for the instrument. Panel A in Column (3) has the second stage result: after being instrumented, the key explanatory variable, PM 2.5, imposes a negative and statistically significant effect on county party secretaries' promotion. This confirms our argument that a better environmental performance is helpful for local officials' promotion. Comparing the coefficient estimations in Column (1) and (3), the smaller magnitude in the OLS estimation may suggest the issue of omitted variables and reverse causality in the estimation.

We also report the reduced form estimation result in Column (2) where we regress political turnover directly on the instrumental variable ($Treatment_c \times post_t$) together with other control variables. The estimated coefficient is also significant, showing that in counties with larger provincial pollution reduction targets, local officials are more likely to get promotion after the implementation of the 11th Five-year Plan.

Table 2. Main results for the effect of PM2.5 on the promotion of county party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM 2.5	-0.799***		-3.435***
	(0.110)		(1.168)
Treatment ×post		0.048***	
		(0.015)	
Panel B: First stage estimation			Dependent variable: PM 2.5
Treatment ×post			-0.014***
			(0.003)
Underidentification test			22.881***
Weak identification test			27.751***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	14,175	14,175	14,175

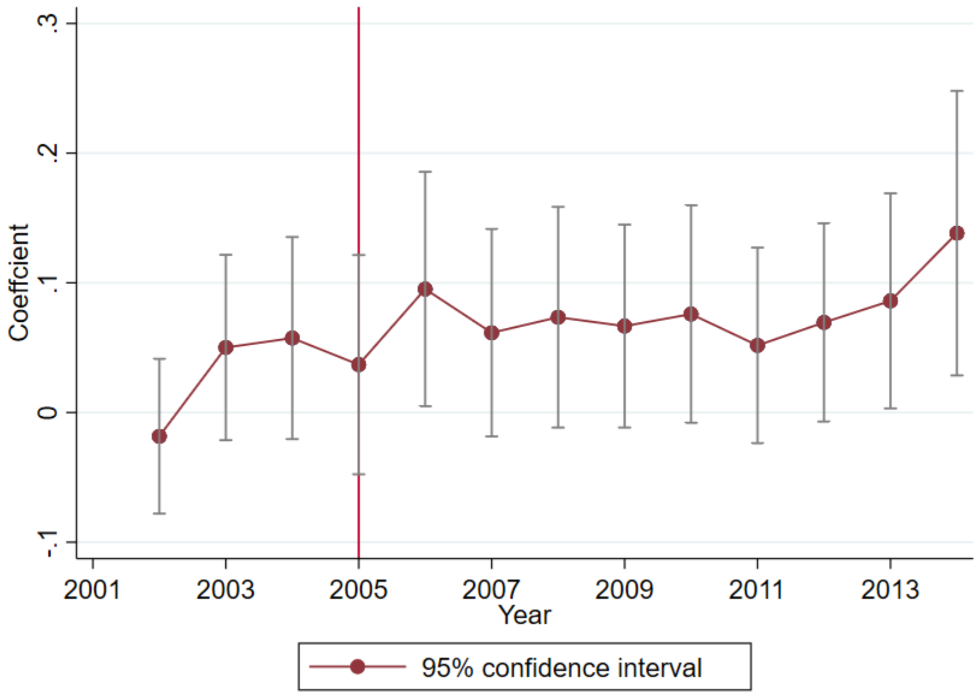
Notes: (1) Robust standard errors, clustered at city level, are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level of departments. Demoted, retired, and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and PM 2.5 at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, and connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014.

Checking Potential Bias Due to Non-random Selection of the Treatment Group: A major source of bias for this difference-in-differences based IV approach is the non-random selection of the treatment (high target) group. In other words, pollution reduction targets were not assigned randomly across provinces. To alleviate this concern, as we discussed earlier, following Gentzkow (2006) and Lu et al. (2017), we identify and control the determinants of the pollution targets. Note if this strategy works, after controlling these target determinants (and other control variables), the treatment and control groups should display a high level of comparability. One way to test this is to verify that counties in provinces with different pollution reduction targets have similar time trends of political turnovers before 2006, conditional on the variables included in the analysis (target determinants plus other controls). Therefore, we estimate the following equation:

$$\text{political turnover}_{ict} = \sum_{t=2001}^{2014} \alpha_t Treatment_c \times \theta_t + \alpha_2 X'_{ct} + \alpha_3 Z'_{ict} + N_c \times f(t) + \eta_c + \theta_t + \vartheta_{ict} \quad (5)$$

α_t is a series of coefficient estimates for year dummies (2001 to 2014) interacted with emission reduction target. This is essentially the reduced form regression from Column (2) of Table 2 but replacing the interaction term between provincial target and a post-2005 dummy with series of interaction terms between provincial target and year dummies.

Figure 2: Effect of emission target on county party secretaries' turnover over time.



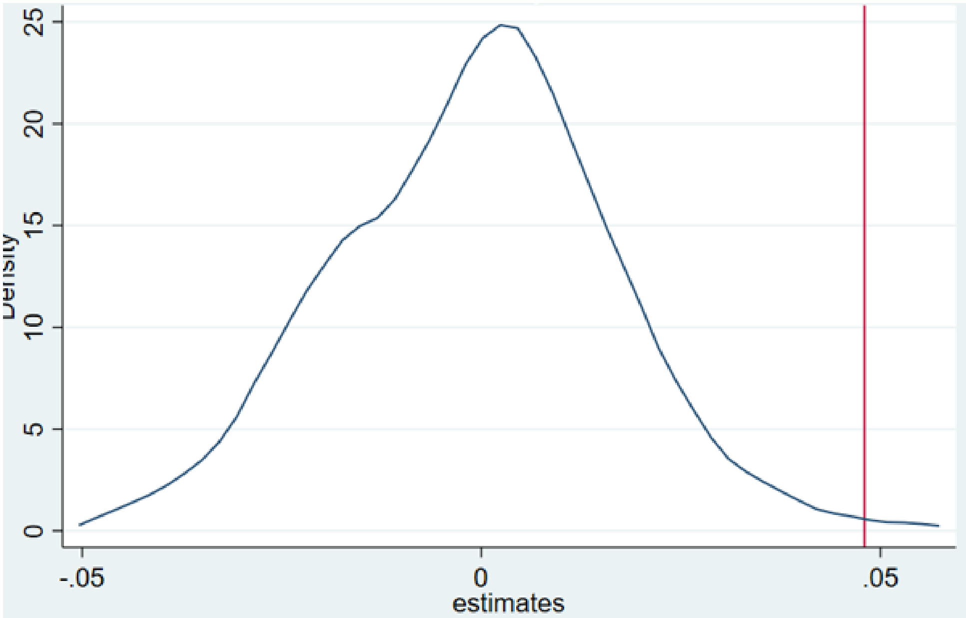
Note: The waved line captures the coefficients of time dummies interacted with emission reduction target. The vertical lines cross each point represent the 95% confidence interval of the estimated effect. The estimation for year of 2001 is the baseline year. The coefficients for year dummies of 2002, 2003, 2004 and 2005 are not significant at 95% confidence interval.

Figure 2 shows differences in promotion chances between the treatment (high targets) and control (low targets) counties over time by plotting the estimated coefficients of α_t. Note that the estimates for 2002-2005 are far from being statistically significant, suggesting the treatment and control groups were balanced in promotion chances before the 11th Five-year Plan (2006-2010), that is, there is a good comparability between the two groups conditional on target determinant variables and other controls in the reduced form regression. From 2006 to 2014, the α_t estimates gradually increase, indicating that pollution reduction targets have a positive effect on promotion chances.

A Placebo Test with Random Assignment of Treatment (Provincial Target): In this section, to further make sure that our analysis does not suffer from biases from omitted variables, we conduct a placebo test, following Chetty et al. (2009), La Ferrara et al. (2012), and Lu et al. (2017). We randomly assign provincial pollution reduction targets to counties and construct a new regressor of interest, $Treatment_c^{false} \times post$. Given the data is randomly assigned, $Treatment_c^{false} \times post$ should produce zero effect on pollution, thus regressing political turnover directly on $Treatment_c^{false} \times post$ (i.e., the reduced form regression) should produce zero effect; otherwise, it indicates the existence of omitted variables.

We conduct this data generating process 500 times to avoid contamination by rare events and to improve the power of the test. Figure 3 shows the distribution of the coefficient estimates of $Treatment_c^{false} \times post$ from the 500 randomized assignments. The estimates are centered around 0, far from our true estimate, 0.048 (from the baseline reduced form regression, i.e., column (2) of Table 2), indicated by a vertical line in the figure. This suggests that the negative and significant effect of pollution on political turnover is unlikely to be driven by unobserved, omitted variables.

Figure 3: The distribution of estimates in the randomization test.



Note: The figure shows the distribution of the estimates from the 500 times of randomization. In this exercise, we randomly assign the degree of changes in SO2 target reduction to provinces (false Target). We then use the baseline reduced form regression to conduct regression analysis based on the false Target. This is repeated 500 times and the resulting estimated coefficients are plotted. The dependent variable is turnover of county party secretaries and the independent variable is false Target × post. The vertical line refers to the true estimates in Column (2) of Table 2, i.e., 0.048.

Main results using SO2

In Table 3, we report the results for the effect of SO2. Column (1) has the results from an OLS estimation, and the coefficient of SO2 is positive. As we have discussed earlier, SO2 can be endogenous due to the issues of omitted variables or reverse causality, thus the estimation can be biased. Once we use ventilation coefficient to instrument SO2 in Column (3), the variable SO2 imposes a negative and statistically significant effect on county party secretary promotion. This is consistent with the results from PM 2.5 regressions. Also note that the first stage result, in Panel B, shows that the instrument, ventilation coefficient, has a negative and statistically significant effect on SO2, suggesting that higher wind speed and higher mixing height reduce pollution levels, proving the relevance condition of the instrument.

We also report the reduced form estimation result in Column (2), where we regress political turnover directly on the ventilation coefficient together with other control variables. The estimated coefficient is also significant as it shows that in the counties with a larger ventilation coefficient (therefore lower pollution all else equal), local officials are more likely to be promoted.

Table 3. Results for the effect of SO2 on promotion of county party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	0.075*		-1.290**
	(0.039)		(0.640)
Ventilation coefficient		0.093**	
		(0.040)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-0.072***
			(0.017)
Underidentification test			20.956***
Weak identification test			18.234***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	10,022	10,022	10,022

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is the Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demoted, retired, and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures, industry production in each county-year, and SO2 emission at city level. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile and smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

6. Robustness Checks

In this section, we present robustness checks to see if our main results hold when we consider alternative operationalization of pollution measures, control for peer and predecessor pollution levels together, account for promotion outcomes in other counties in the same prefecture, limit our analysis to sub-samples of our data, and use simultaneous equations to model promotion alongside local GDP. We also discuss how we further address the reverse causality issue by limiting our analysis to a subset of officials who started their county party secretary posts before environmental performance was added to the cadre evaluation system with the 11th Five-year Plan (2006-2010). Column (1) to (9) in Table 4 and Column (1) to (8) in Table 5 are instrumental variable estimation results; Column (10) in Table 4 and Column (9) in Table 5 are results from simultaneous equation estimation.

Capturing relative performance in pollution reduction

In Column (1) of Table 4, we examine the effect of PM2.5 on political turnovers without controlling city peer performance (PM2.5 in each prefecture/city-year) and predecessor performance (average PM2.5 during the predecessor's tenure). In Column (2) of Table 4, we control for both city peer performance and predecessor performance regarding PM2.5 pollution. The estimates of the instrumented PM2.5 variable in Column (1) and (2) are very similar to the baseline estimation in Table 2.

In Column (3), we consider using one pollution variable to test the relative performance of local officials. This alternative measure is operationalized as follows:

$$\text{Diff\_PM2.5}_{ict} = (\text{PM2.5}_{ct} - \overline{\text{PM2.5}_{c,T-1}}) - (\text{PM2.5}_{pt} - \overline{\text{PM2.5}_{p,T-1}}) \quad (6)$$

On the right hand side, the first term, $\text{PM2.5}_{ct} - \overline{\text{PM2.5}_{c,T-1}}$, is the difference between a county(c)-year(t)'s PM2.5 concentration (PM2.5_{ct}) and the average of PM2.5 concentrations during a county party secretary's predecessor's term ($\overline{\text{PM2.5}_{c,T-1}}$). The idea is to measure how much more air pollution a county has emitted compared to the average level of its party secretary's predecessor. The second term, $\text{PM2.5}_{pt} - \overline{\text{PM2.5}_{p,T-1}}$, is the prefecture version of the first term, i.e., the difference between a prefecture(p)-year(t)'s PM2.5 concentration (PM2.5_{pt}) and the average of PM2.5 annual concentrations during a prefecture party secretary's predecessor's term ($\overline{\text{PM2.5}_{p,T-1}}$): it measures how much more air pollution a prefecture has emitted compared to the average level its prefecture party secretary's predecessor. The difference between these two terms on the right hand side of equation (6) captures a county party secretary's relative yearly PM2.5 air pollution performance compared to his/her predecessor and compared to the relative growth (measured in the same way) at the prefecture level. The higher this value, the worse the environmental performance of a county party secretary compared to his/her predecessor and peers in the same prefecture. Column (3) of Table 4 shows our result holds when we use this Diff_PM2.5_{ict} variable to measure relative PM2.5 pollution directly rather than controlling for peer and predecessor performance as additional variables.

In Column (1), (2), and (3) of Table 5, we repeat the same robust checks for the effect of SO2. When we do not control for city peer performance and predecessor performance, the estimated coefficient of SO2 is also negative and significant in Column (1). In Column (2), when both city peer performance and predecessor performance are included, the coefficient of SO2 is still negative; though the p-value is 0.119, a little larger than the 0.10 threshold, probably due to a much smaller sample size.[16] In Column (3), Diff_SO2_{ict} is negative and significant.[17]

Potential spillover effect

One county party secretary's chances of promotion might also depend on promotion outcomes in other counties in the same prefecture given the total positions for promotion are often relatively stable in the same prefecture. In other words, it is possible that a spillover effect across counties within the same prefecture would occur. We conduct a robustness check by adding a spatial lag of the dependent variable: this is a temporally lagged (by a year, to avoid the simultaneity bias in spatial lag models) average dependent variable value of all other counties in the same prefecture. For PM2.5, the result is reported in Column (4) of Table 4. We find that the coefficient of the instrumented PM 2.5 is still significant and negative; its magnitude is slightly smaller than the baseline result in Column (3) of Table 2.[18]

In Column (4) of Table 5, we examine the spillover effect for SO2 regressions. The coefficient of instrumented SO2 is still negative but it is not significant, with a p-value around 0.20. This lack of statistical significance is likely to be firstly a function of a smaller sample size compared with the PM2.5 case (Column (4) of Table 4); and secondly because of the nature of spatial lag models. In an extreme case, if county party secretaries can only be promoted within the same prefecture and the number of promotions is fixed during a time period, for a given county *c*, the spatial lag variable – which measures promotion outcomes in ALL other counties – can almost perfectly predict its promotion outcome, making other explanatory variables almost irrelevant. However, in the real world, upper-level government officials certainly would not decide promotion for county *c* by only counting promotion outcomes in other counties. In other words, a spatial lag model like ours is a very demanding model for the non-spatial lag explanatory variables (also given that we have controlled for a very large number of fixed unit effects at the same time).

Results using sub-samples

We exclude observations from Hebei province for the Summer Olympic Games venue cities, the observations for officials whose turnover happened during 2008 or 2009 for financial

[16] The sample size drops because of missing information of predecessors, especially for the officials in the early 2000s.

[17] We measure a party secretary's relative air pollution growth the same way as in the case of PM2.5: $\text{Diff\_SO2}=(\text{SO2}_{ct}-\overline{\text{SO2}_{c,T-1}})-(\text{SO2}_{pt}-\overline{\text{SO2}_{p,T-1}})$.

[18] The coefficient of spatial lag itself is -0.448 and significant.

crisis, and counties in provincial capital cities. The estimation results are reported in Column (5), (6), and (7) for PM2.5 in Table 4, and Column (5), (6) and (7) for SO2 in Table 5. The main results stay, indicating that our results are not driven by specific subsamples.

In 1998, a Two Control Zones (TCZ) policy was implemented by the central government with tougher regulations imposed in TCZ cities. This might introduce a further cross-sectional difference regarding the effect of pollution on promotion. We exclude TCZ counties and the results are reported in Column (8) in Table 4 and Table 5. Our results hold. Interestingly, the magnitudes of mean coefficient estimates of the pollution variables in Column (8) in Table 4 (the effect of PM2.5 in non-TCZ counties) and in Column (8) in Table 5 (the effect of SO2 in non-TCZ counties) are larger than those from the full samples (Column (3) in Table 2 and Table 3). This suggests that the pollution-promotion effect is stronger in non-TCZ than in TCZ counties: for the same amount of pollution reduction, party secretaries in TCZ counties were rewarded less than those in non-TCZ counties.

If an upper-level government requires an environmental improvement relative to past performance (e.g., in percentage terms), leaders in counties with past tougher environmental regulations (e.g., TCZ counties) might face a disadvantage because their pollution levels might have already been pushed down to a low level and any further reduction would be very costly; if the upper level government takes this into consideration, the same amount pollution reduction in TCZ counties should be rewarded more: we should see a stronger pollution-promotion effect in TCZ counties.

However, other mechanisms might also be at play here. First, TCZ counties might have already made the required investment in pollution reduction equipment, therefore are better equipped to reduce pollution. Second, their local officials and civil servants might be more experienced and better trained. Finally, they might have not pushed down their pollution to a level beyond which any further reduction would be very costly: this is consistent with recent studies that suggest the TCZ policy had a limited effect on curbing SO2 emissions, especially during the 10th Five-year Plan (2001-2005) (Chen et al. 2018). Under these possibilities, the upper level government might hold a higher standard for local leaders in the TCZ counties: the same amount pollution reduction in TCZ counties should be rewarded less; this is consistent with what we find regarding a weaker pollution-promotion effect in TCZ counties.

Simultaneous equation model estimation

It is possible that industrial activities in some dirty industries will produce higher GDP, thus GDP can be an outcome variable of pollution levels. We have used instrumental variable estimation to control the endogeneity of pollution in the analysis. In this section, as one more robust check, we use a simultaneous equation model taking both GDP per capita and political turnovers as endogenous outcomes. The details for the estimation of simultaneous equations can be found in the online appendix, Section E.

Column (10) in Table 4 is the result from simultaneous equation estimation for PM2.5, which is comprised by two equations that describe the relationships among turnover and GDP per capita. To identify and estimate the simultaneous equations, in estimation for GDP per capita, we control for $Treatment_c \times post_t$ and fiscal expenditures of each county; and in estimation for political turnovers, we control for the average PM2.5 in each city-year. The standard errors are bootstrapped 50 times. The estimated coefficient of PM 2.5 is still significant and negative. We also examine the effect of SO2 using a similar simultaneous equation model. The result is reported in Column (9) of Table 5: the coefficient is not statistically significant.

Table 4. Robust checks for the effect of PM2.5 on promotion of county party secretaries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: Political Turnover	No peer and predecessor	Peer and predecessor	Relative performance	Spatial lag	Exclude Hebei	Exclude 2008 & 2009	Exclude capital city	Exclude TCZ	Confine the sample to leaders who started before 2006	Simultaneous equation
PM 2.5	-3.612***	-3.843**		-3.296**	-4.472***	-4.130**	-4.122***	-4.610***	-5.749*	-0.325***
	(1.249)	(1.615)		(1.532)	(1.504)	(1.754)	(1.279)	(1.529)	(3.083)	(0.068)
Diff_PM2.5_{ict}			-2.699**							
			(1.372)							
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Personal control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Target determinants× T	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Target determinants× T2	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Target determinants× T3	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	14,175	11,054	11,054	11,312	13,405	12,525	13,101	6,846	5,785	14,175

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is the political turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demoted, retired, and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and PM25 at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014. (5) Column (1) to (9) are results using the DID based instrument. Column (10) is the result from simultaneous equation model, and the standard errors are bootstrapped for 50 times.

Table 5. Robust checks for the effect of SO2 on promotion of county party secretaries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: Political Turnover	No peer and predecessor	Peer and predecessor	Relative performance	Spatial lag	Exclude Hebei	Exclude 2008 & 2009	Exclude capital city	Exclude TCZ	Simultaneous equation
SO2	-1.369*	-2.640		-0.744	-1.629*	-2.172*	-1.225*	-2.079*	0.024
	(0.696)	(1.686)		(0.676)	(0.834)	(1.123)	(0.667)	(1.121)	(0.023)
Diff_$SO2_{ict}$			-1.075*						
			(0.648)						
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Personal control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,022	4,599	4,649	7,292	9,245	8,564	9,087	4,742	10,022

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is the Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demoted, retired, and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures, and industry production in each county-year, and SO2 emission at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile or smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients. (6) The p-value for the instrumented SO2 variable in Column (2) is 0.119. (7) Column (9) is the result from simultaneous equation model, and the standard errors are bootstrapped for 50 times.

Addressing a potential reverse causality

A reverse causality threat to our analysis is that higher promotability cadres are appointed to counties with better potentials in environment protection and economic growth. Note that GDP growth has always been important for promotion. Yet before the 11th Five-year Plan (2006-2010), pollution was not a major consideration. If there is such a reverse causality, before 2006, higher promotability cadres were more likely to be assigned to counties with better potential for economic growth, regardless of the potential for environmental protection; after the implementation of the 11th Five-year Plan, environmental protection became an important factor, high promotability cadres who were assigned to counties with high economic growth potential but low pollution reduction potential should have been re-assigned to counties with high potentials for both economic growth and pollution reduction. When we checked our data regarding cadre job transfers, we do not observe this pattern. First, in our data, for county party secretaries, about 18% of job changes are transfers to other counties (still) as party secretaries – there is no significant year-by-year variation in the percentage of such same-level transfers during our study period. Second, we test whether there is any significant difference in air pollution between transfer-source counties and transfer-target counties of these same-level party secretary job transfers; t-test results show that there is indeed no significant difference in the means of air pollution between these two groups of counties (p-value = 0.40 for PM2.5 and p-value = 0.15 for SO2).

However, there is still the possibility that cadres who were newly promoted to the county party secretary level after 2005 were assigned to counties based on their promotability, which introduces the reverse causality. As a robustness check, therefore, we limit our analysis to leaders who were already at the county party secretary level before the 11th Five-year Plan. Column (9) of Table 4 shows that the coefficient of PM2.5 is still statistically significant.

We cannot apply the same strategy to SO2 regressions because there is only one year, 2005, before the 11th Five-year Plan in the SO2 sample. Yet, the instrument, ventilation coefficient, itself helps to address this reverse causality concern. Local ventilation coefficients often exhibit significant year-by-year changes: such temporal changes are a function of meteorological conditions that are difficult to predict for the medium and long terms (e.g., for next month or next year). It is very unlikely for leaders to be able to self-select in and out of counties depending on (poorly predicted) expected year-to-year changes in ventilation coefficients.

7. Testing the Pollution-promotion Link for County Magistrates

Our analysis so far examines political turnovers of county party secretaries. This focus is motivated by the fact that party secretaries are the ones really in charge at every level of the Chinese government. In this section, we extend our analysis to county magistrates who take more responsibility in the day-to-day work of local development. In Table 6, we present the results of OLS, reduced form, and instrumental variable regression regarding the effect of PM2.5: PM2.5 has a negative and statistically significant effect on county magistrates' promotion. Compared to the coefficient for party secretaries in Column (3) of Table 2, the IV estimation for county magistrates is smaller. The total number observations for county magistrates is 11,146, slightly smaller than the number in county party secretary regressions due to more missing personal characteristics of county magistrates.

Table 6. Results for the effect of PM2.5 on promotion of county magistrates.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM25	-0.732***		-2.660**
	(0.128)		(1.211)
Treatment × post		0.052**	
		(0.024)	
Panel B: First stage estimation			Dependent variable: PM25
Treatment × post			-0.020***
			(0.004)
Underidentification test			27.423***
Weak identification test			29.072***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	11,146	11,146	11,146

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is the Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demoted, retired, and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and PM 2.5 at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014.

In Table 7, we report the results for the effect of SO2 on political turnovers of county magistrates. Similarly, we find that SO2 has a negative and statistically significant effect. Compared to the coefficient for county party secretaries in Column (3) of Table 3, the estimation in for county magistrates is slightly larger. In our online appendix, Table A4 and Table A5 present robustness checks with a different operationalization for political turnover, which treats demotion, retirement, and punishment as also 0. The estimation findings are similar to what we find in Table 6 and Table 7 of this section.

Table 7. Results for the effect of SO2 on promotion of county magistrates.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	0.302***		-1.826*
	(0.087)		(1.091)
Ventilation coefficient		0.174**	
		(0.086)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-1.826***
			(1.091)
Underidentification test			25.850***
Weak identification test			21.326***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	6,880	6,880	6,880

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demotion, retirement and punished officials are not included. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, city SO2 emission, the amount of crop production, saving, value added in agriculture production and agriculture machinery power. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile or smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

8. Beyond the County-level: Prefecture and Provincial Party Secretaries

In the hierarchical structure of administrative divisions in China, at the top is the central government, followed by provincial governments, prefecture level governments, and county-level governments. Generally, each level oversees the work carried out by its lower level in the administrative hierarchy. In the introduction, we provided justifications for our focus on county leaders. As far as we know, ours is the first county level study on the pollution-promotion link. One natural question, after we have established a robust causal effect of air pollution on county leaders' promotion, is whether we would find similar results at higher administrative levels. In this section, we examine the effect of environmental performance on prefecture and provincial party secretaries' promotion.

We apply similar estimation strategies. The estimation results for prefecture party secretaries are reported in Table 8 for the effect of PM2.5 and in Table 9 for the effect of SO2. Column (3) of both Table 8 and Table 9 show that after we apply instrumental variable estimation, the effect of environment performance on political turnovers is not statistically significant. The estimation results for province party secretaries are reported in Table 10 for PM2.5 and in Table 11 for SO2. In Column (3) of both tables, the instrumented PM2.5 and SO2 also have no effect on political turnovers.

The effect of environment performance on promotion is statistically significant and robust at the county level. Why don't we find a similar effect at the prefecture and provincial levels? Firstly, a much lower number of observations at the prefecture and provincial level makes it much more difficult to find statistically significant effects, especially given that we include many control variables and fixed effects in the analysis. Secondly, as we discussed in the introduction, county officials are distant in hierarchy and pose very little threat to central rulers; their loyalty therefore matters less than competence which is needed for local economic growth and pollution reduction. The promotions of prefecture and provincial officials are tied more to loyalty because these positions are key to the survival of the central rulers (Landry et al. 2018).

Table 8. Results for effect of PM2.5 on promotion of prefecture party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM25	-0.393		-1.383
	(0.333)		(2.100)
Treatment × post		0.015	
		(0.023)	
Panel B: First stage estimation			Dependent variable: PM25
Treatment × post			-0.013***
			(0.003)
Underidentification test			12.238**
Weak identification test			13.956**
City FE	YES	YES	YES
Year FE	YES	YES	YES
City control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	3,337	3,337	3,337

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is the Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different cities or staying at the same level departments. Demoted, retired and punished officials are not included. (3) City control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each city-year, and PM 2.5 in each province. Personal control variables include official's gender, education, age, age square, tenure length, and connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014.

Table 9. Results for effect of SO2 on promotion of prefecture party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	0.151**		0.319
	(0.055)		(0.349)
Ventilation coefficient		-0.077	
		(0.082)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-0.241***
			(0.043)
Underidentification test			30.111***
Weak identification test			31.344***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	2,448	2,448	2,448

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments. Demotion, retirement and punished officials are not included. (3) City control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each city-year, and SO2 emission each province. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile or smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

Table 10. Results for effect of PM2.5 on promotion of provincial party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM25	-0.659*		-0.092
	(0.333)		(0.757)
Treatment × post		0.000	
		(0.021)	
Panel B: First stage estimation			Dependent variable: PM25
Treatment × post			-0.026***
			(0.005)
Underidentification test			6.430***
Weak identification test			27.528***
Province FE	YES	YES	YES
Year FE	YES	YES	YES
Province control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	331	331	331

Notes: (1) Robust standard errors, clustered at province level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is the Political Turnover which equals to1 if the province official gets the promotion, 0 if moving between different provinces or staying at the same level departments. Demoted and punished officials are not included. (3) Province control variables include log of per capita GDP, fiscal revenue, fiscal expenditure, total population, infrastructure expenditures and industry production in each province-year. Personal control variables include official's gender, education, age, age square, tenure length, connection which is measured by the dummy of central working experiences. The variables to measure target determinants are ventilation coefficient in 2005, desulfurization capacity of desulfurization facilities in 2005, and environment capacity in 2005. (4) The sample period is from 2001 to 2014.

Table 11. Results for effect of SO2 on promotion of provincial party secretaries.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	-0.003		0.442
	(0.114)		(0.556)
Ventilation coefficient		-0.135	
		(0.165)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-0.305***
			(0.103)
Underidentification test			7.559***
Weak identification test			8.821*
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	237	237	237

(1) Robust standard errors, clustered at province level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is Political Turnover which equals to1 if the province official gets the promotion, 0 if moving between different provinces or staying at the same level departments. Demotion and punished officials are not included. (3) Province control variables include log of per capita GDP, fiscal revenue, fiscal expenditure, total population, infrastructure expenditures and industry production in each province-year. Personal control variables include official's gender, education, age, age square, tenure length, connection which is measured by the dummy of central working experiences. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile or smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

9. Conclusion and Discussion

Does it pay to be "greener" as a local official in China? In this paper, we first examine whether local air pollution affects county leaders' chances of promotion. In addition to testing the marginal effect of pollution on promotion, we adopt an instrumental variable approach to deal with potential endogeneity issues of the key independent variables: we use a difference-in-differences based instrument for PM 2.5 and ventilation coefficient for SO2. Our empirical analysis shows that for county party secretaries, those who were able to reduce air pollution are much more likely to be promoted. We find similar results for county magistrates. Yet when we extend our analysis to prefecture and provincial party secretaries, we do not find any empirical evidence for the pollution-promotion link.

Our key empirical findings have important policy implications. First, the Chinese cadre's career incentive structure that was built to promote economic growth has evolved to include other priorities including environmental protection. It has started to reward county leaders who were able to outperform their peers in reducing air pollution. One remaining question is when local officials really must choose between economic development and environmental quality such as in moments during economic crisis, whether they would prioritize development and employment again. The current global pandemic and economic recession seems to present a stern test for local officials in China given Chinese economy's high level of trade-dependence.

Moreover, we find that unlike their county-level counterparts, prefecture and provincial party secretaries' promotions were not based on their environmental performances. We have argued that most day-to-day functions of the government, including environmental protection, are often being implemented by county governments. The fact that county leaders' promotion is tied to environmental performances clearly helps to improved environmental quality in China. However, enforcing the same incentive structure for leaders at the prefecture and provincial levels is also very important. For instance, in China, often the central government sets the environmental policy objectives and assigns provincial targets. In response, provincial governments design their own enforcement plans and allocate the regulatory burdens to cities and counties. A provincial leader may not be the enforcer on the ground, but he/she is the central planner in a province: the extent to which he/she is motivated to improve environmental quality is critical to address the environmental crises in China today.

Finally, there is more research to be done. For instance, more qualitative evidence is needed to shed lights on how county leaders' environmental performances are evaluated. As far as we know, there does not seem to be a nationally unified standard: firm-level emissions, emission concentration measures in waste air and wastewater, blue sky days, and total emissions in a county are all possible targets. Provincial and prefecture governments seem to have some level of flexibility here. Yet the nature of targets matters. For instance, targets requiring reduction to a given level of emissions differ from those requiring an improvement relative to past emission levels (e.g., in percentage terms). This is because the latter approach often would be more costly for counties with lower starting levels of emissions: their emissions have been reduced to a low level beyond which any further reduction would be more difficult.[19]

This paper focuses on the effects of air pollution, which is often more visible and tends to afflict urban areas (Cao and Prakash 2012). Also, thanks to satellite data, we can measure air quality for small localities when monitoring station data is not available. Future research, however, should also investigate the potential effects of water and other types of pollution on promotion given their severities in China. Past empirical research of environmental regulation has overwhelmingly focused on air pollution, water and other types of pollution remain relatively under-studied. Recent research such as Kahn et al. (2015), Chen et al. (2018), and He et al. (Forthcoming), however, have demonstrated the importance of water pollution regulations in China.[20] While more research is certainly needed, we hope this paper has provided a solid foundation for this new and exciting area of research.

[19] We thank one reviewer for reminding us the implications of different evaluating targets.

[20] Also see Dasgupta et al. (2001) for an earlier study.

References

Arya, S. Pal. 1998. Air Pollution Meteorology and Dispersion. New York: Oxford University Press.

Bagayev, Igor, and Julie Lochard. 2017. EU air pollution regulation: A breath of fresh air for Eastern European polluting industries? Journal of Environmental Economics and Management 83: 145-163.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. How much should we trust differences-in-differences estimates? The Quarterly Journal of Economics 119(1): 249–275.

Binder, Seth, and Eric Neumayer. 2005. Environmental pressure group strength and air pollution: An empirical analysis. Ecological Economics 55(4): 527– 538.

Bernauer, Thomas and Vally Koubi. 2009. Effects of political institutions on air quality. Ecological Economics 68(4): 1355-1365.

Broner, Fernando, Paula Bustos, and Vasco M. Carvalho. 2012. Sources of comparative advantage in polluting industries. Working Paper.

Cai, Hongbin, Yuyu Chen, and Qing Gong. 2016. Polluting thy neighbor: unintended consequences of China's pollution reduction mandates. Journal of Environmental Economics and Management 76: 86–104.

Cai, Xiqian, Yi Lu, Mingqin Wu, and Linhui Yu. 2016. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. Journal of Development Economics 123: 73–85.

Cao, Xun, Genia Kostka, and Xu Xu. 2019. Environmental political business cycles: the case of PM2.5 air pollution in Chinese prefectures. Environmental Science & Policy 93: 92–100.

Cao, Xun, and Aseem Prakash. 2012. Trade competition and environmental regulations: domestic political constraints and issue visibility. The Journal of Politics 74(1): 66-82.

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. 2012. Gaming in air pollution data? Lessons from China. The B.E. Journal of Economic Analysis & Policy 13 (3): 1-43.

Chen, Ye, Hongbin Li, and Li-An Zhou. 2005. Relative performance evaluation and the turnover of provincial leaders in China. Economics Letters 88(3): 421-425.

Chen Jie Yvonne, Pei Li, andYi Lu. 2018. Career concerns and multitasking local bureaucrats: evidence of a target-based performance evaluation system in China. Journal of Development Economics 133: 84-101.

Chen, Zhao, Matthew E. Kahn, Yu Liu, and Zhi Wang. 2018. The consequences of spatially differentiated water pollution regulation in China. Journal of Environmental Economics and Management 88: 468-485.

Chen, Xiude, Quande Qin, and Y.-M. Wei. 2016. Energy productivity and Chinese local officials' promotions: Evidence from provincial governors. Energy Policy 95: 103-112.

Chetty, Ray, Adam Looney, and Kory Kroft. 2009. Salience and taxation: theory and evidence. American Economic Review 99: 1145-1177.

Choi, Eun Kyong. 2012. Patronage and performance: Factors in the political mobility of provincial leaders in post-Deng China. China Quarterly 212: 965-981.

Dasgupta, Susmita, Mainul Huq, David Wheeler, Chonghua Zhang. 2001. Water pollution abatement by Chinese industry: cost estimates and policy implications. Applied Economics 33: 547–557.

Dean, Judith M., Mary E. Lovely, and Hua Wang. 2009. Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China. Journal of Development Economics 90: 1–13.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2013. Truth-telling by third-party auditors and the response of polluting firms: experimental evidence from India. Quarterly Journal of Economics 128 (4): 1499–1545.

Economy, Elizabeth C. 2004. The river runs black: the environmental challenge to China's future. Cornell University Press.

Feng, Gen-Fu, Minyi Dong, Jun Wen, and Chun-Ping Chang. 2018. The impacts of environmental governance on political turnover of municipal party secretary in China. Environmental Science and Pollution Research 25: 24668–24681.

Fredriksson, Per G. and Daniel L. Millimet. 2004. Comparative politics and environmental taxation. Journal of Environmental Economics and Management 48: 705–722.

Fredriksson, Per G., Eric Neumayer, Richard Damania, and Scott Gates, 2005. environmentalism, democracy, and pollution control. Journal of Environmental Economics and Management 49 (4): 343-365.

Freeman, Richard, Wenquan Liang, Ran Song, Christopher Timmins. 2019. Willingness to pay for clean air in China. Journal of Environmental Economics and Management 94: 188-216.

Gao, Jie. 2015. Pernicious manipulation of performance measures in China's cadre evaluation system. China Quarterly 223: 618-637.

Ghanem, Dalia, Junjie Zhang. 2014. 'Effortless Perfection:' Do Chinese cities manipulate air pollution data? Journal of Environmental Economics and Management 68: 203–225.

Gentzkow, Matthew. 2006. Television and voter turnout. The Quarterly Journal of Economics 121(3): 931–972.

Grafton, Quentin, and Stephen Knowles. 2004. Social capital and national environmental performance: A cross sectional analysis. Journal of Environment and Development 13(4): 336-370.

Greenstone, Michael, and Kelsey Jack. 2015. Envirodevonomics: A Research Agenda for an Emerging Field. Journal of Economic Literature 53(1): 5–42.

He, Guojun, Shaoda Wang, and Bing Zhang. Forthcoming. Watering down environmental regulation in China. Quarterly Journal of Economics.

Heberer, Thomas, and Anja Senz. 2011. Streamlining local behavior through communication, incentives, and control: a case study of local environmental policies in China. Journal of Current Chinese Affairs 40: 77–112.

Hering, Laura, and Sandra Poncet. 2014. Environmental policy and exports: evidence from Chinese cities. Journal of Environmental Economics and Management 68: 296-318.

Jack, Kelsey. 2017. Environmental economics in developing countries: An introduction to the special issue. Journal of Environmental Economics and Management (86): 1-7.

Jia, Ruixue, Masayuki Kudamatsu, and David Seim. 2015. Political selection in China: The complementary roles of connections and performance. Journal of the European Economic Association 13: 631–668.

Jiang, Junyan. 2018. Making bureaucracy work: Patronage networks, performance incentives, and economic development in China. American Journal of Political Science 62(4): 982–999.

Karplus, Valerie J., and Mengying Wu. 2019. Smoke and mirrors: Did China's environmental crackdowns lead to persistent changes in polluting firm behavior? Working paper.

Kinkel, Jonathan, and William Hurst. 2015. The judicial cadre evaluation system in China: From quantification to intra-state legibility. China Quarterly 224: 933-954.

Kahn, Matthew, Pei Li, and Daxuan Zhao. 2015. Water pollution progress at borders: The role of changes in China's political promotion incentives. American Economic Journal: Economic Policies 7(4): 223-242.

Landry, Pierre. Xiaobo Lü, and Haiyan Duan. 2018. Does performance matter? Evaluating political selection along the Chinese administrative ladder. Comparative Political Studies 51(8): 1074–1105.

La Ferrara, Eliana, Chong Alberto, and Duryea Suzanne. 2012. Soap operas and fertility: evidence from Brazil. American Economic Journal: Applied Economics (4):1–31.

Li, Can, N. Christina Hsu, and Si-Chee Tsay. 2011. A study on the potential applications of satellite data in air quality monitoring and forecasting. Atmospheric Environment 45(22): 3663-3675.

Li, Hongbin, and Li-An Zhou. 2005. Political turnover and economic performance: the incentive role of personnel control in China. Journal of public economics 89(9): 1743-1762.

Li, Xiaoqin, Huashuai Chen, and Yonghui Li. 2020. The effect of air pollution on children's migration with parents: evidence from China. Environmental Science and Pollution Research 27:12499–12513.

Lu, Yi, Zhigang Tao, and Lianming Zhu. 2017. Identifying FDI spillovers. Journal of International Economics 107: 75-90.

Maskin, Eric, Yingyi Qian, and Chenggang Xu. 2000. Incentives, information, and organizational form. The Review of Economic Studies 67: 359–378.

McRae, Shaun. 2015. Infrastructure quality and the subsidy trap. American Economic Review 105(1): 35–66.

Olivier, Jos G. J., and Jeroen A.H.W. Peters. 2018. Trends in global CO2 and total greenhouse gas emissions: 2018 Report. PBL Netherlands Environmental Assessment Agency, the Hague.

Opper, Sonja, and Stefan Brehm. 2007. Networks versus performance: political leadership promotion in China. Department of Economics, Lund University. Working paper.

Payne, Roger. 1995. Freedom and the Environment. Journal of Democracy 6(1): 41-55.

Pu, Zhengning, and Jiasha Fu. 2018. Economic growth, environmental sustainability, and China mayors' promotion. Journal of Cleaner Production 172: 454-465.

Shapiro, Judith. 2012. China's environmental challenges. Polity.

Shen, Hongtao, and Zhou Yankun. 2017. Environmental law enforcement supervision and corporate environmental performance: Quasi-natural experimental evidence from environmental interviews. Nankai Business Review 20(6): 73-82.

Shi, Xinzheng and Zhufeng Xu. 2018. Environmental regulation and firm exports: Evidence from the eleventh Five-Year Plan in China. Journal of Environmental Economics and Management 89: 187-200.

Shih, Victor, Wei Shan, and Mingxing Liu. 2010. Gauging the elite political equilibrium in the CCP: A quantitative approach using biographical data. China Quarterly 201(3): 79-103.

Shih, Victor, Adolph, Christopher, and Mingxing Liu. 2012. Getting ahead in the communist party: explaining the advancement of central committee members in China. American Political Science Review 106(1): 166-187.

Streets, David, Timothy Canty, Gregory Carmichael, Benjamin de Foy, Russell Dickerson, Bryan Duncan, David Edwards, John Haynes, Daven Henze, Marc Houyoux, Daniel Jacob, Nickolay Krotkov, Lok Lamsal, Yang Liu, Zifeng Lu, Randall Martin, Gabriele Pfister, Robert Pinder, Ross Salawitch, and Kevin JWecht. 2013. Emissions estimation from satellite retrievals: A review of current capability. Atmospheric Environment 77: 1011-1042.

Tilt, Bryan. 2013. Industrial pollution and environmental health in rural China: risk, uncertainty, and individualization. China Quarterly 214: 283-301.

Wang, Chunhua, JunJie Wub, and Bing Zhang. 2018. Environmental regulation, emissions and productivity: Evidence from Chinese COD-emitting manufacturers. Journal of Environmental Economics and Management 92: 54-73.

Wang, Xin, and Ping Lei. 2020. Does strict environmental regulation lead to incentive contradiction? — Evidence from China. Journal of Environmental Management 269.

Wu, Mingqin, and Bin Chen. 2016. Assignment of provincial officials based on economic performance: Evidence from China. China Economic Review 38: 60–75.

van der Kamp, Denise. 2018. Can ‘police patrols’ prevent pollution? The limits of top-down bureaucratic control in China. Working paper.

Yin, Haitao, Xuemei Zhang, and Feng Wang. 2019. Environmental regulations in China. Oxford Research Encyclopedia of Environmental Science.

Zhang, Bing, Xiaolan Chen, and Huanxiu Guo. 2018. Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China. Journal of Public Economics 164: 70–90.

Zheng, Siqi, Matthew E. Kahn, Weizeng Sun, and Danglun Luo. 2014. Incentives for China's urban mayors to mitigate pollution externalities: The role of the central government and public environmentalism. Regional Science and Urban Economics 47: 61–71.

Zhu, Shengjun, Canfei He, and Ying Liu. 2014. Going green or going away: Environmental regulation, economic geography and firms’ strategies in China’s pollution-intensive industries. Geoforum 55: 53–65

Zuo, Cai. 2015. Promoting city leaders: the structure of political incentives in China. China Quarterly 224: 955-984.

Online Appendix

Section A: Extra Summary Statistics and Robustness Checks.

TableA1. Summary statistics for variables of target determination.

Variables	Definition	Mean	S.td.	Obs.
SO2_2005	SO2 concentration in 2005 in each province	0.439	0.457	14,175
PM2.5_05	PM2.5 in 2005 in each province	3.476	0.586	14,175
Capacity	Environment capacity in 2005 measured by SO2 emission in each province, 10000 tons (log)	4.571	0.285	14,175
Dust	Ratio of industrial dust emission up to the standard in 2005 in each province (%)	73.447	18.809	14,175
Soot	Ratio of industrial soot emission up to the standard in 2005 in each province (%)	81.258	13.017	14,175
Industrial SO2	Industrial SO2 emission in 2005 in each province, tons (log)	13.661	0.466	14,175
GDP	Provincial GDP per capita in 2005 in each province, yuan (log)	8.765	0.681	14,175
Population	Provincial population in 2005 in each province, 10000 persons (log)	8.765	0.681	14,175
Waste gas	Operating cost of waste gas treatment in 2005 in each province, 10000 yuan (log)	11.467	0.887	14,175
Investment projects	Investment on environment protection projects in 2005 in each province, 10000 yuan (log)	2.536	0.809	14,175
Waste processing	Expenditures on waste processing in 2005 in each province, 10000 yuan (log)	11.012	0.891	14,175
Desulfurization	Desulfurization capacity of desulfurization facilities in 2005 in each province, tons/hour (log)	5.529	1.216	14,175
Facilities	Number of waste gas treatment facilities in 2005 in each province (log)	8.474	0.646	14,175
Reduction SO2	Reduction of industrial SO2 emission in 2005 in each province, tons (log)	12.793	0.816	14,175
Geographical	It is 1 if in eastern regions, and 0 otherwise	0.284	0.451	14,175
Ventilation	Ventilation coefficient in 2005 in each province (log)	7.355	0.247	14,175

TableA2. Results for promotion of county party secretaries using a new political turnover variable: the PM2.5 case.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM25	-0.733***		-3.423***
	(0.105)		(1.173)
Treatment ×post		0.048***	
		(0.015)	
Panel B: First stage estimation			Dependent variable: PM 2.5
Treatment ×post			-0.014***
			(0.003)
Underidentification test			22.650***
Weak identification test			27.301***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	14,896	14,896	14,896

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments, demoted, retired, or punished. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and PM 2.5 at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014.

Table A3. Results for promotion of county party secretaries using a new political turnover variable: the SO2 case.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	0.091***		-1.136*
	(0.033)		(0.614)
Ventilation coefficient		0.081**	
		(0.038)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-0.071***
			(0.019)
Underidentification test			22.255***
Weak identification test			19.686***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	10,609	10,609	10,609

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments, demoted, retired, or punished. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and SO2 emission at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile and smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

TableA4. Results for promotion of county magistrates using a new political turnover variable: the PM2.5 case.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
PM25	-0.718***		-2.701**
	(0.127)		(1.226)
Treatment ×post		0.052**	
		(0.024)	
Panel B: First stage estimation			Dependent variable: PM25
Treatment ×post			-0.014***
			(0.003)
Underidentification test			26.838***
Weak identification test			28.806***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Target determinants× T	YES	YES	YES
Target determinants× T2	YES	YES	YES
Target determinants× T3	YES	YES	YES
Observations	11,344	11,344	11,344

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments, demoted, retired, or punished. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and PM 2.5 at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. Target determinants includes environment quality, environment capacity, emission base, economic development, pollution reduction capability and geographical factors. The variables used to measure target determinants are SO2 concentration in 2005, PM 2.5 in 2005, environment capacity in 2005, industrial SO2 emission in 2005, the ratio of industrial dust emission up to the standard in 2005, the ratio of industrial soot emission up to the standard in 2005, provincial GDP in 2005, provincial population in 2005, the operating cost of waste gas treatment in 2005, investment on environment protection projects in 2005, expenditures on waste processing in 2005, desulfurization capacity of desulfurization facilities in 2005, the number of waste gas treatment facilities in 2005, the reduction of industrial SO2 emission in 2005, ventilation coefficient in 2005, and geographical locations. (4) The sample period is from 2001 to 2014.

Table A5. Results for promotion of county magistrates using a new political turnover variable: the SO2 case.

	OLS	Reduced form	IV
	(1)	(2)	(3)
Panel A: Second stage estimation		Dependent variable: Political Turnover	
SO2	0.295***		-1.747*
	(0.084)		(1.019)
Ventilation coefficient		0.172**	
		(0.084)	
Panel B: First stage estimation			Dependent variable: SO2
Ventilation coefficient			-0.099***
			(0.019)
Underidentification test			27.816***
Weak identification test			23.125***
County FE	YES	YES	YES
Year FE	YES	YES	YES
County control variables	YES	YES	YES
Personal control variables	YES	YES	YES
Observations	7,014	7,014	7,014

Notes: (1) Robust standard errors, clustered at city level, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 if moving between different counties or staying at the same level departments, demoted, retired, or punished. (3) County control variables include log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, and SO2 emission at each city each year. Personal control variables include official's gender, education, age, age square, tenure length, connection. (4) The sample period is from 2005 to 2014. (5) Instrument is ventilation coefficient. The counties whose ventilation coefficients are larger than 95 percentile and smaller than 5 percentiles are dropped to delete the effect of extreme ventilation coefficients.

Section B: Potential Sources of Cross-sectional Variation during the Post-2005 Period.

Table B-1: Pollution Reduction Targets from the 11th Five-Year Plan (unit: 10,000 tons).

Province	SO2 emissions in 2005	SO2 emission targets in 2010		Reduction Percentage (%)
		Total	In which: Electricity sector	
Beijing	19.1	15.2	5	20.4
Tianjin	26.5	24	13.1	9.4
Hebei	149.6	127.1	48.1	15
Shanxi	151.6	130.4	59.3	14
Neimenggu	145.6	140	68.7	3.8
Liaoning	119.7	105.3	37.2	12
Jilin	38.2	36.4	18.2	4.7
Heilongjiang	50.8	49.8	33.3	2
Shanghai	51.3	38	13.4	25.9
Jiangsu	137.3	112.6	55	18
Zhejiang	86	73.1	41.9	15
Anhui	57.1	54.8	35.7	4
Fujian	46.1	42.4	17.3	8
Jiangxi	61.3	57	19.9	7
Shandong	200.3	160.2	75.7	20
Henan	162.5	139.7	73.8	14
Hubei	71.7	66.1	31	7.8
Hunan	91.9	83.6	19.6	9
Guangdong	129.4	110	55.4	15
Guangxi	102.3	92.2	21	9.9
Hainan	2.2	2.2	1.6	0
Chongqing	83.7	73.7	17.6	11.9
Sichuan	129.9	114.4	39.5	11.9
Guizhou	135.8	115.4	35.8	15
Yunan	52.2	50.1	25.3	4
Tibet	0.2	0.2	0.1	0
Shaanxi	92.2	81.1	31.2	12
Guansu	56.3	56.3	19	0
Qinghai	12.4	12.4	6.2	0
Ningxia	34.3	31.1	16.2	9.3
Xinjiang	51.9	51.9	16.6	0

Source: "Reply to *Pollution Control Plan During the Eleventh Five-Year Plan,*" issued by the China State Council in 2006.

Table B2: list of TCZ cities.

Province	TCZ city	Province	TCZ city	Province	TCZ city	Province	TCZ city
Beijing	Beijing		Yangzhou	Henan	Zhengzhou	Guangxi	Nanning
Tianjin	Tianjin				Luoyang		Liuzhou
Hebei	Shijiangzhuang		Zhenjiang		Anyang		Guilin
	Tangshan		Taizhou		Jiaozuo		Wuzhou
	Handan	Zhejiang	Hangzhou		Sanmenxia		Guigang
	Xingtai		Ningbo	Hubei	Wuhan		Yulin
	Baoding		Wenzhou		Huangshi		Hezhou
	Zhangjiakou		Jiaxing		Yichang		Hechi
	Chengde		Huzhou		Ezhou	Chongqing	Chongqing
	Hengshui		Shaoxing		Jingmeng	Sichuan	Chengdu
Shanxi	Taiyuan		Jinhua		Jingzhou		Zigong
	Datong		Quzhou		Xianning		Panzhihua
	Yangquan		Taizhou	Hunan	Changsha		Luzhou
	Shuozhou	Anhui	Wuhu		Zhuzhou		Deyang
	Yuncheng		Manshan		Xiangtan		Mianyang
	Xinzhou		Tongling		Hengyang		Suining
	Linfen		Huangshan		Yueyang		Neijiang
Inner Mongolia	Huhehaote		Xuancheng		Changde		Leshan
	Baotou	Fujian	Fuzhou		Zhangjiajie		Nanchong
	Wuhai		Xiamen		Yiyang		Yibin
	Chifeng		Sanming		Chenzhou		Guangan
Liaoning	Shenyang		Quanzhou		Huaihua		Meishan
	Dalian		Zhangzhou		Loudi	Guizhou	Guiyang
	Anshan		Longyan	Guangdong	Guangzhou		Zunyi
	Fushun	Jiangxi	Nanchang		Shaoguan		Anshun
	Benxi		Pingxiang		Shenzhen	Yunnan	Kunming
	Jinzhou		Jiujiang		Zhuhai		Qujing
	Fuxin		Yingtan		Shantou		Yuxi
	Liaoyang		Ganzhou		Foshan		Zhaotong
	Huludao		Ji’an		Jiangmen	Shaanxi	Xian
Jinlin	Jilin	Shandong	Jinan		Zhanjiang		Tongchuan
	Siping		Qingdao		Zhaoqing		Weinan
	Tonghua		Zibo		Huizhou		Shangluo
Shanghai	Shanghai		Zaozhuang		Shanwei	Gansu	Lanzhou
Jiangsu	Nanjing		Yantai		Qingyuan		Jinchang
	Wuxi		Weifang		Dongguan		Baiyin
	Xuzhou		Jining		Zhongshan		Zhangye
	Changzhou		Taian		Chaozhou	Ningxia	Yinchuan
	Suzhou		Laiwu		Jieyang		Shizuishan
	Nantong		Dezhou		Yunfu	Xinjiang	Wulumuqi

Section C: Satellite vs. Government Data and Potential Biases for Our Analysis. One might question whether the use of satellite data is appropriate when a county leader's superior only has official pollution data which can suffer from data manipulation. In this section, we justify the use of satellite data by showing 1): there is simply no official-report data on air pollution at the county level; 2): satellite data of air pollution is highly correlated with official monitoring station data when looking at prefecture cities; and probably more importantly 3): with a downward manipulation in the official pollution data, the use of satellite data would be biased against us finding a negative relationship between pollution and a leader's chances of promotion. We explain these three points in turn in the following.

1). No available county level official air pollution data: there is no official air pollution data at the county level. Even at the prefecture-city level, official air pollution data from monitoring stations is only available since very recently. According to Freeman et al. (2019): "Existing studies of air pollution in China typically use the Air Pollution Index (API) and PM10 data from the Ministry of Environmental Protection of China. However, API and PM10 data can only be obtained in large and medium-sized cities in China, and PM2.5 data were not published until 2014."[21]

In the absence of official county level data, we need air pollution data that can be considered good proxy for the official data. Satellite data have been used in many studies as a good measure for local air pollution. For example, in Freeman et al. (2019): "…We collect city level annual average PM2.5 using Global Annual PM2.5 Grids derived from satellite data by Van Donkelaar et al. (2016). These data provide a reliable and accurate measurement of air quality for all cities in China." As the quote above indicates, satellite data provides a reliable and accurate measurement of air quality in China.

2): High correlations between satellite and monitoring station data: we checked the correlations between satellite and monitor station data. The only open source monitoring station data that we are aware of is from the Chinese Air Quality Historical Database.[22] These are daily data for a number of air pollutants such as AQI, PM2.5, PM10, SO2, CO, NO2, and O3, based on government monitoring station data for prefecture/cities in China, 2013-2018 (by the time we scraped the website in 2019). Note that for 2013, there are not enough days covered by the data, so it is problematic to aggregate the 2013 daily data for annual averages. Even for 2014, not all days are available for all prefectures. The PM2.5 satellite data we use are for 1998-2016; the SO2 satellite data we use are for 2004-2018.

We take correlations between SO2 reported by government monitoring station – using annual averages of daily means from the Chinese Air Quality Historical Database – and the SO2 satellite data used in this study, for prefecture cities and years covered by both data sources: these are 326 prefecture cities and for 2014-2017. The correlation is 0.714. We conducted the same exercise for PM2.5: these are the same 326 prefecture cities and for

[21] The Chinese city statistical yearbooks have data on the volume of SO2 exhausted (ton) since 2003 for many prefecture cities: but these are industrial sources of SO2 only.

[22] 中国空气质量历史数据: https://www.aqistudy.cn/historydata.

2014-2016. The correlation is 0.681. Both correlations are very high, indicating that satellite data is indeed a very good proxy for government monitoring station data.

3): Potential biases introduced by data manipulation in the official pollution data: What if some county officials manipulated air pollution data reported to higher level governments? How would it bias our results? Here, it is reasonable to assume data manipulation by local officials is a downward change in the reported data. Moreover, there are two likely scenarios regarding the real relationship between pollution and promotion; we consider each of these two scenarios and show how a downward change in the reported air pollution data by local officials would bias our result.

(Note that there is a third possible but very unlikely scenario in which there is a positive relationship between pollution and promotion: this is highly unlikely as it implies that upper level governments, after controlling for other factors such as economic growth and personal connections, would promote leaders who can generate more pollution. We therefore do not consider this unlikely scenario in the following.)

a. *In the real world, there is no relationship between pollution and promotion*: we play out this scenario by the top row figures in next page of this memo. The question is that given there is no real relationship between pollution and promotion, whether we would have found a negative relationship if some counties manipulate pollution data. The short answer is no: if there really is no relationship between these two variables, even with data manipulation by county officials, with the satellite air pollution data we use, we won't able to find a (false) negative relationship. The reason is the following:

   Figure a1 from the top row represents the hypothetical real relationship: we only show 8 data points for the sake of simplicity; x-axis represents pollution level, y-axis the probability of promotion. There is a vertical line (in red) that we use to represent a hypothetical warning line set by an upper-level government: this is the threshold of pollution that county governments are not supposed to go over.

   Chen et al. (2012) and Ghanem and Zhang (2014) both suggest that data manipulation happens often in the form of local governments changing pollution statistics downward from above the warning line to below the warning line to avoid punishment: this results in the truncation in pollution data, by which scholars can detect data manipulation. This data manipulation is captured by Figure a2 on the top row: two solid points on the far right side of the figure are moved horizontally to the left of the warning line: we indicate this move by two gray arrows in the figure. Because there is no relationship between pollution and promotion, there is no change in the y-axis values for these two data points – this is the reason why these are purely horizontal moves. Note that Figure a2 is the data observed by the upper level government. (We also display the previous positions of these two points by two gray hollow points: they are not observed by the upper level government.)

   Because we use satellite data where there is no manipulation, so we cannot observe Figure a2 on the top row; what we observe is Figure a3: here, pollution values are the real values from the satellite – same as in Figure a1; the values for promotion probabilities are the same as in Figure a2, which are also the ones from Figure a1 because manipulating pollution data has no effect on promotion. Therefore, Figure a1 and Figure a3 are identical. Analyzing Figure a3 is the same as analyzing Figure a1; it introduces no bias because all three figures indicate that there is no relationship between pollution and promotion, which is the real relationship we assumed in this scenario.

b. *In the real world, there is a negative relationship between pollution and promotion*: we play out this scenario in the three figures of the bottom row of Figure 1. We ask a similar question as in the previous scenario: what kind of bias would be introduced if there is data manipulation by county officials and we use satellite data? The short answer is under this scenario, when there is a downward data manipulation in air pollution data, and if we find a negative relationship between pollution and promotion by analyzing our data, the real relationship should be even more negative between pollution and promotion. In other words, data manipulation by county officials is biased against us finding our key empirical result. The reasoning is the following:

In the bottom row, Figure b1 represents the hypothetical real relationship: note we draw a right-downward dash line to represent the real relationship between pollution and promotion – this is what we want to recover from our analysis. Again, Chen et al. (2012) and Ghanem and Zhang (2014) suggest that data manipulation happens in the form of local governments changing pollution statistics from above to below the warning line. This data manipulation is captured by Figure b2: the two data points at far-right side are moved to the left of the warning line. Because there is a negative relationship between pollution and promotion, such downward manipulation in pollution data creates an upward change in the y-axis values for these two data points: this is the reason why they are moved to their upper left – this is the data observed by the upper level government.

Because we use satellite data where there is no manipulation, we cannot observe Figure b2. What we observe is Figure b3: here, pollution values (x-axis) are the real values from satellite – same as in Figure b1 (real relationship), but different from Figure b2 (data observed by upper level government after manipulation); the values for promotion probabilities are the same as in Figure b2: a downward data manipulation by county officials increases the chances of promotion and we can only observe these promotion outcomes affected by such data manipulation.

Therefore, Figure b3 (data we use) and Figure b1 (real relationship) differs only in the y-axis values for the two observations on the far-right side of the figures: in Figure b3, these two data points are moved upwards vertically, therefore flattening the relationship at the higher value end of x-axis; if we fit linear regression line now based on data in Figure b3 – this is the one we recover from our analysis, indicated by a long dash line in Figure b3 – it is more flattened than the real relationship between pollution and promotion (indicated by a dash line in all three figures). In other words, when the real relationship between pollution and promotion is negative and when there is a downward manipulation in pollution data, and if we find a negative relationship by analyzing our data (Figure b3), the real relationship between pollution and promotion (Figure b1) should be even more negative. Data manipulation by county officials is therefore biased against us finding our key empirical result.

Figure C1: Analyzing potential biases by data manipulation in the official data.

a): in the real world, there is no relationship between pollution and promotion.

b): in the real world, there is a negative relationship between pollution and promotion.

Section D: An alternative DID estimation.

In this section, we present results from an earlier version of the paper in which a difference-in-differences (DID) approach is used instead of the instrumental variable approach currently used in the main text of the paper. We decided to only present this DID approach in an online appendix because first, our key explanatory variables, local PM2.5 and SO2, might be endogenous. Second, we observe a pre-trend when we test the parallel trend assumption using the full sample: we have an explanation on why we observe this pre-trend; following this explanation, we limit our sample to non-TCZ counties and this pre-trend disappears.

Measuring County Party Secretary Promotion

We use two dependent variables to measure promotion patterns. The first has three values defined as follows:

$$TurnOver1=\begin{cases} 2: promotion\ (move\ from\ county\ to\ district; from\ county\ and\ distritc\ to\ prefecture\ and\ above); \\ 1: job\ move\ at\ the\ same\ level; \\ 0: demotion, retirement, punishment. \end{cases}$$

The second dependent variable is binary and is defined as follows:

$$TurnOver2=\begin{cases} 1: promotion\ (from\ county\ and\ distritc\ to\ prefecture\ and\ above); \\ 0: move\ from\ county\ to\ district;\ job\ move\ at\ the\ same\ level;\ demotion, retirement, punishment. \end{cases}$$

$TurnOver1$ is a more detailed operationalization than $TurnOver2$. In the following discussion, we present empirical results and focus our discussion using $TurnOver1$ as the dependent variable even though using $TurnOver2$ gives similar results.[23] Moreover, whether retirement should be coded as 0 or simply removed from our data is debatable. Removing retired party secretaries from our sample do not change our results though.

Measuring Relative Local Pollution Growth

Using PM2.5 data aggregated at the county-year level, we measure a party secretary's relative yearly environmental performance as follows:

$$\text{Diff\_PM2.5}_{ict} = (\text{PM2.5}_{ct} - \overline{\text{PM2.5}_{c,T-1}}) - (\text{PM2.5}_{pt} - \overline{\text{PM2.5}_{p,T-1}})$$

On the right hand side, the first term, $\text{PM2.5}_{ct} - \overline{\text{PM2.5}_{c,T-1}}$, is the difference between a county(c)-year(t) PM2.5 concentration (PM2.5_{ct}) and the average of PM2.5 annual concentrations during a county party secretary's predecessor's term ($\overline{\text{PM2.5}_{c,T-1}}$). The idea here is to measure how much more a county has emitted air pollution, for a given year, compared to the average level of air pollution of a party secretary's predecessor. The second term, $\text{PM2.5}_{pt} - \overline{\text{PM2.5}_{p,T-1}}$, is the prefecture version of the first term: the difference between a prefecture(p)-year(t) PM2.5 concentration (PM2.5_{pt}) and the average of PM2.5 annual concentrations during a prefecture party secretary's predecessor's term ($\overline{\text{PM2.5}_{p,T-1}}$); in other words, $\text{PM2.5}_{pt} - \overline{\text{PM2.5}_{p,T-1}}$ measures how much more a prefecture has emitted air pollution compared to the average level of air pollution of a prefecture party secretary's predecessor.

---

[23] Tables and results available upon request from authors.

The difference between these two terms then captures a county party secretary's relative yearly PM2.5 air pollution growth/performance compared to his/her predecessor and compared to the relative growth (measured in the same way) at the prefecture level. The higher this value, the worse the environmental performance of a county party secretary compared to his/her predecessor and peers in the same prefecture. Finally, using SO2 data at the county-year level, we measure a party secretary's yearly relative air pollution growth the same way as in the case of PM2.5:

$$\text{Diff\_SO2}=(\text{SO2}_{ct}-\overline{\text{SO2}_{c,T-1}})-(\text{SO2}_{pt}-\overline{\text{SO2}_{p,T-1}}).$$

Control Variables

In addition to relative pollution growth variables, we include a battery of county characteristic variables, including log per capita GDP, fiscal revenue, total population, infrastructure expenditures, and industry production in each county-year as well as county party secretary leader characteristics such as gender, education, age, age square and tenure length. We also control for the mean PM2.5 or SO2 in each prefecture-year. Table D1 presents the basic summary statistics for variables included in the main analysis.

Table D1. Summary statistics for the key variables

Variables	Definition	Mean	S.td.	Number of observations
Dependent variables				
Promotion1	Termination or Retirement=0; Same level=1; County to district or Promotion=2	0.3483	0.7161	20597
Promotion2	Promotion=1, all others=0	0.1260	0.3319	20597
Independent variables				
Diff_PM2.5	$=(\text{PM2.5}_{ct}-\overline{\text{PM2.5}_{c,T-1}})-(\text{PM2.5}_{pt}-\overline{\text{PM2.5}_{p,T-1}})$	-0.3087	0.9067	15012
Diff_SO2	$=(\text{SO2}_{ct}-\overline{\text{SO2}_{c,T-1}})-(\text{SO2}_{pt}-\overline{\text{SO2}_{p,T-1}})$	0.0177	2.0325	5450
Control variables				
Gender	1=female, 2=male	1.9683	0.1751	19644
Education	0=Associate degree or even below, 1= Bachelor degree, 2=Master degree, 3= Doctor degree.	1.5330	0.6669	18109
Age	Age of official in each year	46.8825	3.9396	18825
Age2	Age's square of official in each year	2213.488	366.7468	18825
Tenure	The years spent at one tenure	4.1394	1.7552	23597
$\Delta RGDP$	The growth rates of GDP per capita in each county-official-year	0.1590	0.2260	13907
MPM2.5	the mean PM2.5 in each prefecture city-year	234.1369	200.367	20597
MSO2	the mean So2 in each prefecture city-year	2.9504	4.3249	11239
lnRGDP	Log of per capita GDP in each county-year	9.3720	0.9297	20184
lnFisrev	Log of fiscal revenue in each county-year	9.7921	1.3294	19168
lnPop	Log of total population in each county-year	3.6804	0.7608	20505
lnIfexp	Log of infrastructure expenditures in each county-year	11.8713	1.7512	20423
lnIndus	Log of industry production in each county-year	12.1247	1.5018	20493

Main Results

To test the marginal effect of relative pollution growth on county party secretary's chances of promotion, we first estimate the following model:

$$TurnOver_{ict} = \alpha \text{Diff\_PM2.5}_{ict}/\text{Diff\_SO2}_{ict} + \beta \Delta RGDP_{ct} + \gamma X_{ct} + \lambda Z_{it} + \eta_c + \theta_t + \varepsilon_{ict} \quad (1)$$

Note that we use *i* to indicate officials, *c* for county, and *t* for year. When we use SO2 to measure relative pollution growth (Diff_SO2_{ict}), the sample period covered is 2005-2014; when using PM2.5 (Diff_PM2.5_{ict}), it is 2001-2014. Again, $TurnOver_{ict}$ captures the county-year level promotion outcome. $\Delta RGDP_{ct}$ is the growth rates of GDP per capita in each county-year, often used to test the competence hypothesis. X_{ct} includes prefecture and county-year level control variables and Z_{it} party secretary(-year) control variables. We include fixed county (η_c) and fixed year (θ_t) effects. We cluster the standard errors at the county level (ε_{ict}).

Table D2: Linear probability model (OLS estimation).

VARIABLES	Political Turnover (Termination or Retirement=0; Same level=1; County to district or Promotion=2)					
	Sample period: 2001-2014			Sample period: 2005-2014		
	(1)	(2)	(3)	(4)	(5)	(6)
Diff_PM2.5	-0.0847***	-0.1013***	-0.2358***			
	(0.0085)	(0.0099)	(0.0258)			
Diff_SO2				-0.0170**	-0.0210**	-0.1818***
				(0.0069)	(0.0010)	(0.0351)
County variables	NO	NO	YES	NO	NO	YES
Personal variables	NO	YES	YES	NO	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.0994	0.1365	0.2409	0.1961	0.2132	0.3722
Observations	14990	13106	7791	5319	4731	1948

Notes: (1) Robust standard errors, clustered at county, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is the promotion which equals two if the official gets the promotion or move from the county to district, equals one if moving between different county or the same level departments, and equals zero for others. (3) Control variables includes the mean PM2.5 or So2 in each prefecture city-year, the average growth rate of per capital GDP and log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, also includes official's gender, education, age, age square and tenure length.

Table D2 reports the basic findings regarding the marginal effect of relative pollution growth, with model specification 1-3 using the relative PM2.5 pollution growth variable and specification 4-6 the relative SO2 pollution growth variable. All model specifications are estimated with fixed county (County FE) and fixed year (Year FE) effects: the differences are in model 1 and 4, we do not include county and personal control variables; model 2 and 5 add in personal controls; and model 3 and 6 have both county and personal controls. We do have many missing values from the county control variables. Therefore, once county controls are added as in model 3 and 6, the number of observations drop significantly. Here, we find that regardless of the model specifications and types of air pollution, the relative growth in air pollution is always negatively associated with promotion and this association is always statistically significant.

After establishing our baseline result of a negative and statistically significant association between relative growth in air pollution and chances of promotion in Table D2, we conduct a difference-in-differences (DID) regression as specified as follows:

$$TurnOver_{ict} = \alpha' \text{Diff\_PM2.5} \times \text{Post}_{2005} + \alpha \text{Diff\_PM2.5} + \beta \Delta RGDP_{ct} + \gamma X_{ct} + \lambda Z_{it} + \eta_c + \theta_t + \varepsilon_{ict} \quad (2)$$

Post_{2005} equals to 1 for post 2005 years and 0 otherwise. $\text{Diff\_PM2.5} \times \text{Post}_{2005}$ is the DID estimator variable (and the only difference between equation 1 and 2). Post_{2005} only shows up in the DID estimator variable, because it itself is absorbed by the year fixed effects. The coefficient of $\text{Diff\_PM2.5} \times \text{Post}_{2005}$, that is, α', captures the causal effect of relative pollution growth on promotion in this DID set up: this is the difference between the effect of relative pollution growth on promotion since the 11th Five Year Plan and the effect of relative pollution growth on promotion in the pre-11th Five Year Plan period. Note that there is no SO2 data from the pre-11th Five Year Plan period. Therefore, our DID regressions are limited to PM2.5. However, PM2.5 and SO2 are highly correlated: correlations are higher than 0.6 when looking at the data yearly. Therefore, PM2.5 is a good proxy for SO2.

The first model specification of Table D3 reports a statistically significant DID estimator ($\text{Diff\_PM2.5} \times \text{I(year>2005)}$) coefficient. Model specification 2 of Table D3 further disaggregate the Post_{2005} variable into year dummy variables and interact them with the PM2.5 pollution relative growth variable. Here, the estimates on the coefficients associated with the *lags* – the interactions between year dummies after 2005 and relative pollution growth – are all negative and statistically significant except the one with year 2006: this makes sense because 2006 is the first year for the 11th Five-Year Plan. This might have been the transition year during which policy changes were introduced and implemented.

Importantly, model specification 2 of Table D3 helps us to test the parallel trend assumption in DID. Intuitively, the idea here is that one can include the interactions of the year dummies and the treatment variable (relative pollution growth) for all the periods except one (due to the dummy variable trap). If the outcome trends between treatment and control group before the treatment are the same, that is, the parallel trend assumption holds, the coefficients associated with the *leads* – the interactions between year dummies before 2006 and relative pollution growth – should all be statistically insignificant, i.e., the difference in differences is not significantly different in the pre-treatment periods.

In model specification 2 of Table D3, the coefficient estimates for the leads show signs of a pre-trend. First, the coefficient for the 2002 lead ($\text{Diff\_PM2.5} \times \text{I(year=2002)}$) is statistically significant at the 0.10 level. Moreover, the slowly declining mean coefficient estimates of the leads of 2002, 2003, and 2004 – 0.184, 0.090, 0.068 – also suggest a pre-trend. It seems that the effects of pollution on promotion has been trending down since 2002 before the treatment of the 11th Five-year Plan kicked in 2006.

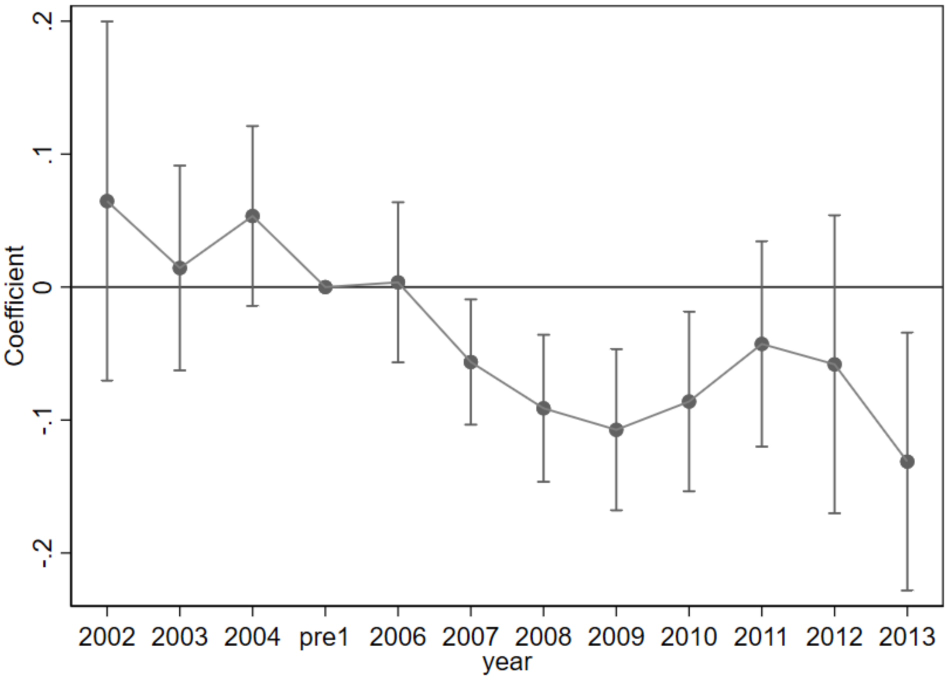
A potential reason for the pre-trend is that before the 11th Five-year Plan, the central government had implemented policy schemes such as the TCZ to address pollution issues in certain areas: local leaders in those areas were subject to performance evaluation based on their environmental performances before 2006; in other words, long before the beginning of the 11th Five-year Plan, certain regions of the country (e.g., the TCZ counties) were already moving towards a cadre evaluation system that incorporates environmental quality; this can result in a pre-trend. If this explanation is valid, once we remove the TCZ counties – again, those that were subject to higher environmental standards and whose leaders were subject to pollution-based promotion before 2006 – the pre-trend should be weakened. Figure D1 shows the results after we remove TCZ counties from the analysis: we observe a much-weakened pre-trend.

Table D3: Difference-in-differences estimation and pre-trend test.

VARIABLES	Political Turnover (Termination or Retirement=0; Same level=1; County to district or Promotion=2)	
	(1)	(2)
Diff_PM2.5	-0.1439***	-0.170***
	(0.0309)	(0.043)
Diff_PM2.5× I(year>2005)	-0.1214***	
	(0.0316)	
Diff_PM2.5× I(year=2002)		0.184*
		(0.110)
Diff_PM2.5× I(year=2003)		0.090
		(0.066)
Diff_PM2.5× I(year=2004)		0.068
		(0.056)
Diff_PM2.5× I(year=2006)		0.003
		(0.046)
Diff_PM2.5× I(year=2007)		-0.100**
		(0.045)
Diff_PM2.5× I(year=2008)		-0.177***
		(0.052)
Diff_PM2.5× I(year=2009)		-0.206***
		(0.050)
Diff_PM2.5× I(year=2010)		-0.175***
		(0.054)
Diff_PM2.5× I(year=2011)		-0.100*
		(0.057)
Diff_PM2.5× I(year=2012)		-0.143**
		(0.063)
Diff_PM2.5× I(year=2013)		-0.262***
		(0.068)
County variables	YES	YES
Personal variables	YES	YES
County FE	YES	YES
Year FE	YES	YES
R-squared	0.2422	0.2475
Observations	7791	7791

Notes: (1) Robust standard errors, clustered at county, are reported in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Dependent variable is the promotion which equals two if the official gets the promotion or move from the county to district, equals one if moving between different county or the same level departments, and equals zero for others. I(•) is the indicate function equals one if the condition is established in the parentheses and zero otherwise. (3) Control variables includes the mean PM2.5 in each prefecture city-year, the average growth rate of per capital GDP and log of per capita GDP, fiscal revenue, total population, infrastructure expenditures and industry production in each county-year, also includes official's gender, education, age, age square and tenure length.

Figure D1: Time trend test after removing TCZ counties.



The waved line captures the coefficients of time dummies interacted with the variable "Diff_PM2.5". The vertical lines cross each point represent the 95% confidence interval of the estimated effect. Dependent variable is Political Turnover which equals to1 if the official gets the promotion, 0 otherwise, and officials who are demoted, retired, or punished are excluded. Counties in TCZ region are excluded.

Section E: Simultaneous question estimation.

In this section, we estimate the effect of pollution on political turnovers using simultaneous equation estimation as a robustness check. In our baseline estimation, we include GDP per capita and other variables at county level as control variables. It is possible that industrial activities in some dirty industries will produce higher GDP, thus GDP can be an outcome variable of pollution. Including GDP in the regression will induce a bad-control issue and inconsistency in estimation. However, omitting it will apparently induce omitted variable bias. Therefore, we run a simultaneous equation model taking both GDP and political turnover as endogenous outcomes.

$$\text{political turnover}_{ict} = \alpha_1 \text{PM2.5}_{ict} + \alpha_2 GDP_{ict} + \alpha_3 {X_1}'_{ct} + \alpha_4 Z'_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \quad (1)$$

$$\text{GDP}_{ict} = \beta_1 \text{PM2.5}_{ict} + \beta_2 \text{political turnover}_{ict} + \beta_3 {X_2}'_{ct} + \beta_4 Z'_{ict} + \eta_c + \theta_t + \vartheta_{ict} \quad (2)$$

In equation (1), the dependent variable, $\text{political turnover}_{ict}$, is the political turnover of county official *i* in county *c* in year *t*. The explanatory variables include environmental performance, PM2.5_{ict}, i.e., PM2.5 of county official *i* in county *c* in year *t*, and GDP_{ict}, i.e., GDP per capita of official *i* in county *c* in year *t*. X_{1ct} is a vector of time-varying county characteristics, such as fiscal revenue, total population, infrastructure expenditures, and industrial production. Z_{ict} is a vector of time varying characteristics of local officials, such as gender, education, age, age square, tenure length, and connection. We also control for the average PM2.5 in each city-year. η_c is county fixed effect, capturing all time-invariant differences across counties, and θ_t is year fixed effect, capturing all yearly factors that are common to counties such as macro-level shocks. ε_{ict} is error term.

In equation (2), the dependent variable, GDP_{ict}, is GDP per capita of county official *i* in county *c* in year *t*. The explanatory variables include PM2.5_{ict}, political turnover_{ict}, and control variables at county level, X_{2ct}, which includes a vector of time-varying county characteristics, such as fiscal revenue, total population, infrastructure expenditures, and industrial production. $Treatment_c \times post_t$ and fiscal expenditures of each county are also included as control variables. We also control for county fixed effect and year fixed effect. ϑ_{ict} is error term.

To identify and estimate the simultaneous equations, note that X_{1ct} and X_{2ct} are different, in equation (2) we control for $Treatment_c \times post_t$ and fiscal expenditures of each county, while in equation (1), we control for the average PM2.5 in each city-year. The empirical results are shown in Column (10) of Table 4 of the main manuscript.

Similarly, we estimate a simultaneous equation model taking both GDP and promotion as endogenous outcomes when we examine the effect of SO2 on political turnovers.

$$\text{political turnover}_{ict} = \alpha_1 \text{SO2}_{ict} + \alpha_2 GDP_{ict} + \alpha_3 X_1{'}_{ct} + \alpha_4 Z'_{ict} + \eta_c + \theta_t + \varepsilon_{ict} \quad (3)$$
$$\text{GDP}_{ict} = \beta_1 \text{SO2}_{ict} + \beta_2 \text{political turnover}_{ict} + \beta_3 X_2{'}_{ct} + \beta_4 Z'_{ict} + \eta_c + \theta_t + \vartheta_{ict} \quad (4)$$

To identify and estimate the simultaneous equations, X_{1ct} and X_{2ct} are different; in equation (4) we control for ventilation coefficient and fiscal expenditures of each county, together with fiscal revenue, total population, infrastructure expenditures, and industrial production in X_{2ct}. While in equation (1), we also control the average PM2.5 in each city-year besides X_{1ct} and Z_{ict}. The empirical results are shown in Column (9) of Table 5 of the main manuscript.

References:

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. 2012. Gaming in air pollution data? Lessons from China. The B.E. Journal of Economic Analysis & Policy 13 (3): 1-43.

Freeman, Richard, Wenquan Liang, Ran Song, Christopher Timmins. 2019. Willingness to pay for clean air in China. Journal of Environmental Economics and Management 94: 188-216.

Ghanem, Dalia, Junjie Zhang. 2014. 'Effortless Perfection:' Do Chinese cities manipulate air pollution data? Journal of Environmental Economics and Management 68: 203–225.