Decomposing PM_{2.5} air pollution rebounds in Northern China before COVID-19

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Abstract

China's efforts to curb air pollution have drastically reduced its concentrations of fine particulate matter (PM_{2.5}) from 2013 to 2018 nationwide. However, few studies examined the most recent changes in PM_{2.5} concentrations and questioned if the previous PM_{2.5} declining trend was sustained or not. This study took a deep dive into the PM_{2.5} trend for 136 northern cities of China from 2015 to early 2020 before the coronavirus disease 2019 (the COVID-19 hereafter) crisis, using ground-based PM_{2.5} data notably adjusted for a key measurement method change. We find that mean PM_{2.5} concentrations in northern China increased by 5.16 µg/m³ in 2019, offsetting 80% of the large reduction achieved in 2018. The rebound was more significant during the heating seasons (HS; Nov to next Mar) over the 2 years: 10.49 µg/m³ from the 2017 HS to the 2019 HS. A multiple linear regression analysis further revealed that anthropogenic factors contributed to around 50% of the PM_{2.5} rebound in northern cities of China. Such a significant role of anthropogenic factors in driving the rebound was tightly linked to deep cuts in PM_{2.5} concentrations in the previous year, systemic adjustment of policy targets and mitigation measures by the government, and the rising marginal cost of these measures. These findings suggest the need to chart a more sustainable path for future PM_{2.5} emission reductions, with an emphasis on key regions during key pollution periods.

Keywords PM_{2.5} rebound · Northern China · Heating season · Human factors

Introduction

Air pollution is a key environmental threat to human health worldwide (Cohen et al. 2017; Burnett et al. 2018). In China, long-term exposure to fine particulate matter (PM_{2.5}) may have caused 1.5 to 2 million premature deaths annually

(Liang et al. 2020), prompting the government to place air pollution control as a top priority in its policy agenda. Since 2013, the central government has promulgated two large-scale national action plans to tackle the PM_{2.5} air pollution problem: first the 2013–2017 Air Pollution Prevention and Control Action Plan (the 2013–2017 Action Plan hereafter) with ambitious reduction targets set to be achieved by the end of 2017, and then the Three-year Action Plan to Win the Blue-Sky Defense War (2018–2020) as a spinoff (Feng et al. 2019; Li et al. 2020b; Jiang et al. 2021). These two national movements together with stringent enforcement have reduced PM_{2.5} concentrations and improved the air quality greatly (Zheng et al. 2018; Ma et al. 2019; Editorial 2019), and the annual average PM_{2.5} concentrations declined by 34–49% across China from 2013 to 2018 (Zhang et al. 2019b).

However, few studies have examined the post-2018 changes in PM_{2.5} concentrations in China in detail (Zhai et al. 2019; Chen et al. 2020; Bae et al. 2021) (see Table 3 for more detail), or questioned if PM_{2.5} concentration levels had continued to decline after the successful experience by the Action Plan (Yin and Zhang 2020; Zhong et al. 2021).

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One recent study on the PM_{2.5} pollution in Beijing-Tianjin-Hebei and the surrounding areas (the so-called “2 + 26” cities) estimated that PM_{2.5} concentration levels increased by 6.8 µg/m³ (9.46%) in the winter of 2018 (Dec–Feb). More recently, a few studies discovered that PM_{2.5} air pollution also deteriorated during the coronavirus disease 2019 (the COVID-19 hereafter) epidemic in early 2020 (Wang et al. 2020a; Le et al. 2020). However, one big issue with these studies was that such a rebound in PM_{2.5} air pollution was more than 100% attributed to meteorological conditions, and human efforts continued to reduce PM_{2.5} concentrations (Yin and Zhang 2020). These results and conclusions run contrary to the observation that government policies and actions may have been relaxed after the great success in 2017 (Ministry of Ecology and Environment of China 2017, 2018, 2019). According to the official statistics (Ministry of Ecology and Environment of China 2020), the national average PM_{2.5} concentration levels in 2019 stayed the same as that in 2018, both at 36 µg/m³, pointing to a strong possibility of a reversed trend for at least some regions.

Our study aims to reassess the changes in China's PM_{2.5} pollution from 2018 to early 2020 before the outbreak of COVID-19 based on a large sample of cities with adjusted PM_{2.5} data and decompose the relative contributions of the meteorological and anthropogenic factors to the recent changes. The contributions of our study are threefold: First, by focusing on the most polluting areas in China with district heating in the north of the Huai River (Ebenstein et al. 2017), we expand the study area to 136 cities in 15 heating provinces in northern China from 2015 to early 2020 right before the COVID-19 crisis. Second, we adjust the PM_{2.5} concentration data following the official monitoring method change for comparison consistency (see “Materials and methods” for more detail). Third, we apply a stepwise multiple linear regression (MLR) analysis (Li et al. 2019a, 2020a; Zhai et al. 2019; Chen et al. 2020; Bae et al. 2021) to decompose PM_{2.5} changes into contributions from meteorological and anthropogenic factors. We further relate the human factor contributions to actual policy adjustment and the rising marginal cost of these policy measures.

Materials and methods

Ground-based PM_{2.5} data with qualitative adjustment

We used data of 136 northern cities with central heating in China. These cities spread over 15 northern provinces: Beijing, Tianjin, Hebei, Shanxi, Heilongjiang, Jilin, Liaoning, Inner Mongolia, Shandong, Henan, Shaanxi, Ningxia, Gansu, Qinghai, and Xinjiang (Fig. 1). Among those 136 cities, “2 + 26” cities were the most polluted area in China, and

the targeted region by the Ministry of Ecology and Environment to mitigate PM_{2.5} pollution in February 2017 (Ministry of Ecology and Environment of China 2017); other northern cities were not targeted at this time. Given the heterogeneity in these two regions, below we analyze the changes in PM_{2.5} concentrations of “2 + 26” cities and other northern cities separately.

The data source for ground-based PM_{2.5} concentrations is an online platform (<https://www.aqistudy.cn/historydata/>), which has been used by several studies before (Zhang et al. 2019c; Zhu et al. 2020). This data source collects real-time data of national monitoring sites from the Ministry of Ecology and Environment of China (<https://www.mee.gov.cn/hjzl/>) and then calculates monthly mean PM_{2.5} concentrations for each city in China. For the purpose of this research, we collected monthly PM_{2.5} concentrations data for each northern city from 2015 to early 2020 before the COVID-19 crisis.

The biggest challenge to use ground-based PM_{2.5} concentrations data is that the Ministry of Ecology and Environment changed its monitoring method of PM_{2.5} concentrations in September 2018 (Li et al. 2020a), so that PM_{2.5} concentration data are not directly comparable before and after September 2018. According to the Amendment for Ambient Air Quality Standards (hereafter referred to as “the Amendment”), the local ambient state instead of the standard state (273 K, 1013 hPa) should be used during the monitoring process of PM_{2.5} concentrations before this Amendment. The local ambient state refers to the real-time condition of monitoring stations, i.e., real-time temperature and surface pressure. Thus, to achieve a consistently measured time series of PM_{2.5} concentrations, we followed the literature (Laugier and Garai 2007; Li et al. 2020a) and applied the Ideal Gas Equation of State to adjust pre-September 2018 PM_{2.5} concentration data:

$$PM_{adj} = PM_{obs} \times \frac{273+0}{273+T} \times \frac{Pressure}{1013} \quad (1)$$

where PM_{adj} and PM_{obs} are PM_{2.5} concentrations with and without adjustment, respectively; T is the real-time temperature, and $Pressure$ is the real-time surface pressure. Since the temperature and surface pressure should be roughly the same within a city, we directly applied the above adjustment to our city-level PM_{2.5} concentration data.

Meteorological data

We integrated meteorological data from several sources. Meteorological variables were mainly from *Airwise*, an online data platform (<http://hz.zc12369.com/home>) that has been used by previous research (Xu et al. 2020; Li et al. 2020b). The original data source of *Airwise* is the ground-based data from the National Meteorology Center (NMC) of

Fig. 1 Changes in mean $PM_{2.5}$ concentrations in northern China from 2016 to 2019. **a–c** Inter-annual changes in northern China between two consecutive years. **d** Time trend in $PM_{2.5}$ concentrations for all northern cities and “2+26” cities. Ground-based $PM_{2.5}$ data from 136 northern cities were used here (for the other 19 cities in northern China, data were imputed from their direct neighbors and then

used in the maps). The 2019 heating season excludes post-Feb 2020 data since the lockdown measures led to considerable $PM_{2.5}$ reductions. Rectangles in a–c indicate the Beijing-Tianjin-Hebei region and the surrounding areas (i.e., the “2+26” cities), and shaded areas in **d** denote the heating seasons

China (<http://www.nmc.cn/>). This platform collects the real-time data of national sites from NMC and provides monthly meteorological data for 137 northern cities from 2015 to 2020. We used six meteorological variables including mean temperature, humidity, wind speed, surface pressure, total precipitation, and total cloud cover. We chose these variables since they are strongly correlated with $PM_{2.5}$ concentrations (Xu et al. 2018; Liu et al. 2020). To fill in possible missing values, we further collected surface pressure data from the China Meteorological Data Service Center (<http://data.cma.cn>; last accessed: 2020–10–17) and the National Climate Data Center (<https://quotsoft.net/air/#archive>; last accessed: 2020–11–25). We also collected three more meteorological variables used in the sensitivity analyses (described below): 850 hPa meridional wind velocity (V850), 10 m meridional wind (V10), and zonal wind (U10), all from MERRA-2 reanalysis by NASA Global Modeling and Assimilation Office (<https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2>, last accessed: 2021–01–10). The MERRA-2 data have a spatial

resolution at $0.5^\circ \times 0.625^\circ$ and we further averaged these data to the city level.

Multiple linear regression model

Several studies have applied stepwise MLR models to quantify the relative impacts of meteorological and anthropogenic factors on air pollutant trends (Li et al. 2019a, 2020a; Zhai et al. 2019). We employed the same method to estimate the contributions of human and nature factors to the $PM_{2.5}$ rebound. First, we regressed monthly $PM_{2.5}$ concentrations on six meteorological variables from February 2017 to January 2020, which are highly relevant to $PM_{2.5}$ concentrations. We specified the following MLR model for each city:

$$PM_{adj} = \beta_0 + \sum_{k=1}^6 \beta_k X_k + \varepsilon \quad (2)$$

where PM_{adj} is the monthly mean $PM_{2.5}$ concentrations after adjusting, X_1 – X_6 are six meteorological variables as described above, and β_k are the corresponding regression coefficients.

We further conducted a series of sensitivity analyses by adding more meteorological variables as well as the second order effect of all variables into the regression. Specifically, we added V850, V10, and U10 into the baseline model. Since V850 has a strong correlation with $PM_{2.5}$ concentrations in Northern China, we also ran a MLR model with V850 and our first six meteorological variables (Cai et al. 2017). For all model runs at the city level, only the first three key variables based on R -square were kept in the final regression to avoid overfitting (Li et al. 2020a). These three key variables varied from one city to another (Supplementary Figs. S1–3). The fitted values of the MLR model reflect the contributions from meteorological factors.

To estimate the contributions from anthropogenic factors, we further distilled the nonlinear trend in the residuals from the MLR model. Specifically, we included seven dummy variables in the regression of MLR residuals from the last step:

$$Res = \alpha_0 + \sum_{k=1}^7 \alpha_k T_k + \epsilon \quad (3)$$

where Res is the residual from Eq. (2) and T_1 – T_7 are time-dummy variables covering the whole study period and indicating whether each month belongs to the heating season or non-heating season in a specific year (e.g., 2017 heating season and 2017 non-heating season, and so on). The regression coefficients α_k are the anthropogenic contributions for each season.

Results

$PM_{2.5}$ pollution rebounds in northern China

Annual mean $PM_{2.5}$ concentrations in northern cities declined from 2015 to 2018 but rebounded in 2019. Table 1

shows that the annual mean $PM_{2.5}$ concentrations in northern China dropped continuously from 2015 to 2018, with a total effect of $16.56 \mu\text{g}/\text{m}^3$. However, this declining trend was reversed in 2019, when $PM_{2.5}$ concentrations increased by $5.16 \mu\text{g}/\text{m}^3$ (14.60%), or 80% of the reduction ($6.4 \mu\text{g}/\text{m}^3$) achieved in 2018. Figure 1c further shows that such a $PM_{2.5}$ rebound in 2019 occurred to most cities in northern China, though some of them continued to reduce their $PM_{2.5}$ concentrations in 2019, such as Beijing (Li et al. 2020b). The rebound was even more significant during the heating seasons (HS; Nov to next Mar) when the $PM_{2.5}$ pollution was the most severe (Fig. 1d). In the 2018 HS, northern cities saw the $PM_{2.5}$ concentrations rebounded by $5.71 \mu\text{g}/\text{m}^3$ (10.80%) after a drastic drop of $16.17 \mu\text{g}/\text{m}^3$ in the 2017 HS (Table 1). However, $PM_{2.5}$ concentrations declined remarkably in the 2019 HS due to the impact of COVID-19 lockdown (Supplementary Table S1) (Huang et al. 2021), resulting in a smaller rebound in northern cities during 2017–2019 HS (Supplementary Table S2). Given that lockdown only had a short-term impact on $PM_{2.5}$ trends (Lu et al. 2021), we excluded its impacts by removing data in February and March 2020 (post-Feb 2020) from the baseline results. As such, $PM_{2.5}$ rebound continued into the 2019 HS, with the $PM_{2.5}$ concentrations further increased by $4.79 \mu\text{g}/\text{m}^3$ (8.1%). These two rebounds increased $PM_{2.5}$ concentrations by $10.49 \mu\text{g}/\text{m}^3$ and offset 65% of the largest reduction in $PM_{2.5}$ concentrations during the 2017 HS.

The so-called “2 + 26” cities, consisting of Beijing, Tianjin, and 26 surrounding cities in Northern China, are the key area in China’s air pollution control program since 2013, and also the targeted region in the annual action plan during heating seasons since 2017. Compared with other northern cities, “2 + 26” cities had a greater drop of $26.67 \mu\text{g}/\text{m}^3$ (33.43%) in their annual mean $PM_{2.5}$ concentrations from 2015 to 2018, but with a smaller rebound of $3.02 \mu\text{g}/\text{m}^3$ (5.68%) in 2019 (Table 1). During heating seasons, these 28 cities also reduced their $PM_{2.5}$ concentrations much more than other cities in the 2017 HS and then experienced a greater rebound in $PM_{2.5}$ pollution in the 2018 HS. Mean

Table 1 Year-to-year changes in mean and max $PM_{2.5}$ concentrations for different time ranges from 2015 to early 2020 in northern China

Time ranges	Mean changes ($\mu\text{g}/\text{m}^3$)				Max changes ($\mu\text{g}/\text{m}^3$)			
	2016–2015	2017–2016	2018–2017	2019–2018	2016–2015	2017–2016	2018–2017	2019–2018
Whole year (Jan–Dec)								
Northern cities	−4.36	−5.80	−6.40	5.16	−5.23	−11.63	−14.74	12.12
“2 + 26” cities	−6.86	−10.24	−9.57	3.02	−0.23	−28.20	−30.61	13.93
Other northern cities	−3.79	−4.80	−5.68	5.64	−6.38	−7.87	−11.17	11.71
Heating season (Nov–next Mar)								
Northern cities	−0.29	−16.17	5.71	4.79	−5.55	−24.87	9.97	7.33
“2 + 26” cities	3.64	−32.06	7.30	2.14	−2.48	−57.18	14.60	6.48
Other northern cities	−1.18	−12.59	5.35	5.38	−6.25	−17.52	8.93	7.52

PM_{2.5} concentrations in the 2018 HS increased by 7.30 $\mu\text{g}/\text{m}^3$ (9.62%) compared to the previous year (Supplementary Fig. S4). Such a rebound effect continued into the 2019 HS (2.14 $\mu\text{g}/\text{m}^3$, 2.57%). These two rebounds together offset 29.44% of the biggest reduction of 32.06 $\mu\text{g}/\text{m}^3$ in the 2017 HS. Other northern cities had an even larger and more evenly distributed rebounding effect over the two heating seasons: 5.35 $\mu\text{g}/\text{m}^3$ in the 2018 HS and 5.38 $\mu\text{g}/\text{m}^3$ in the 2019 HS.

It is worth noting that the maximum of PM_{2.5} concentrations consistently show greater rebound than the means, implying that the PM_{2.5} rebound made the worst pollution month even worse (Table 1).

Decomposing PM_{2.5} rebounds into anthropogenic and meteorological factors

We decomposed the contribution of meteorological and anthropogenic factors to the rebound of PM_{2.5} concentrations using a stepwise MLR model (Li et al. 2019a), one of the two common methods used in this task (see Table 3 for our summary). The results showed that anthropogenic factors contributed to 55% (2.82 $\mu\text{g}/\text{m}^3$) of the PM_{2.5} rebound in northern cities from 2018 to 2019, while meteorological factors only contributed to 45% (2.34 $\mu\text{g}/\text{m}^3$) of the rebound (Fig. 2e). A similar pattern appeared over the 3-year heating seasons from 2017 to 2019, though with a much larger absolute rebound (Fig. 2f). For the “2+26” cities, around 40–50% of the PM_{2.5} rebound was attributed to

anthropogenic factors, and the rebound during the heating seasons was much larger, too. Results from sensitivity analyses with respect to variable choices and functional forms further show a range of 50–60% of human contributions for northern cities, and 20–80% for “2+26” cities from 2018 to 2019 (Supplementary Table S3). Our decomposition results are also robust even if post-Feb 2020 data are included in the analysis (Supplementary Table S3).

The contributions of anthropogenic drivers in different cities varied greatly. For the 136 northern cities used in our MLR model, the contributions of anthropogenic drivers to PM_{2.5} rebound during the 2017–2019 HS ranged from −10.82 to 32.73 $\mu\text{g}/\text{m}^3$, and 112 of them had seen positive contributions of anthropogenic factors to the PM_{2.5} rebound (Supplementary Fig. S6). Considering the important role of anthropogenic factors in PM_{2.5} rebound, we focus on the adjustment of policy targets and mitigation measures below, which would directly affect emissions from human activity. That being said, the underlying physical and chemical mechanisms of PM_{2.5} rebounds also merit further investigation.

Correlation of PM_{2.5} rebounds with previous reduction

The significant PM_{2.5} rebound driven by anthropogenic factors in the heating seasons was tightly linked to the significant reduction of PM_{2.5} before. Anthropogenic contributions

Fig. 2 Decomposition of the relative impact of anthropogenic and meteorological factors on changes in PM_{2.5} concentrations. **a–d** Monthly anomalies (de-measured) of observed and fitted PM_{2.5} concentrations in all northern cities and “2+26” cities either annually or for the heating seasons (HS: Nov, Dec, Jan, Feb, and Mar). **e–h** Decom-

position results in all northern cities and “2+26” cities either annually or for the heating seasons only. The 2019 heating season excludes post-Feb 2020 data since the lockdown measures led to considerable PM_{2.5} reductions

As for other northern cities, the magnitude of the rebounding effect due to human factors in the 2018 HS was also negatively related to their contribution to the reduction in PM_{2.5} concentrations in the previous year. Specifically, for 1 µg/m³ reduction in PM_{2.5} concentrations resulting from human factors in the 2017 HS, PM_{2.5} concentrations

Policy and cost reasons behind PM_{2.5} rebounds

2018–2017 Heating Season

Change in $PM_{2.5}$ ($\mu g/m^3$)

Distance to Beijing (km)

2017–2016 Heating Season

Change in $PM_{2.5}$ ($\mu g/m^3$)

Distance to Beijing (km)

Figure 1 is a scatter plot showing the relationship between the change in mean PM_{2.5} from 2016 to 2017 (X-axis) and the change in mean PM_{2.5} from 2017 to 2018 (Y-axis). The X-axis ranges from -40 to 20, and the Y-axis ranges from -10 to 15. The plot includes data for three groups of cities: "2+26" cities (red triangles), other cities (blue circles), and northern cities (black dashed line). Regression lines are shown for each group: $Y = -0.3 - 0.26X$ for "2+26" cities, $Y = 1.1 - 0.20X$ for other cities, and $Y = 1.4 - 0.18X$ for northern cities. A vertical dashed line is at $X = 0$ and a horizontal dashed line is at $Y = 0$.

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Fig. 5 A comparison of official policy target and mitigation measures for the PM_{2.5} air pollution control in the “2 + 26” cities during the heating seasons from 2017 to 2019. The data are obtained from Ministry of Ecology and Environment of China (2017, 2018, 2019)

	2017	2018	2019
<i>Policy target</i>	PM _{2.5} concentrations and severe haze-polluted days down by more than 15%.	PM _{2.5} concentrations and severe haze-polluted days down by 3%.	PM _{2.5} concentrations and severe haze-polluted days down by 4% and 6%, respectively.
<i>Coal-to-gas & Coal-to-power</i>	Complete the task of coal-to-gas and coal-to-power. Remove scattered coal use Completely.	Use electricity, gas, coal and heat in their best way. Replace scattered coal first in regions with largest impact.	Use technologies that are sustainable, effective, reliable, and popular with the residents.
<i>Staggered industrial production</i>	Shut down production in the building materials industry and VOC-related industries.	Plan staggered production in industrial enterprises according to local conditions.	Exempt A-level firms from reducing emissions, and B-level firms partially reduce their emissions.
<i>Phase out coal-fired boilers</i>	Phase out all 44,000 coal-fired boilers in the elimination list, and hold local officials accountable.	Implement heating supply plans according to local conditions. Speed up the construction of central heating pipe network, and prioritize clean heating methods to eliminate coal-fired boilers.	
<i>Dust control</i>	Suspend all earthwork and house demolition during the heating season with a few exceptions.	Establish a credit management system for the construction industry and a blacklist of some construction market entities.	

increased flexibility and freedom were consistent with the observed rebounding effect of PM_{2.5} concentrations and the significant role of human factors in the “2 + 26” cities during the heating seasons, irrespective of the influence of natural factors. One possible reason for the systemic policy re-adjustment after 2017 was due to the economic losses born by local governments to achieve the milestone targeted by the Action Plan (Li et al. 2019c). Moreover, the policy re-adjustment for “2 + 26” cities in the 2018 HS might contribute to the greater PM_{2.5} rebound than that of other northern cities.

The rising marginal cost of PM_{2.5} mitigation measures was also astonishing. As illustrated in Fig. 6, only four out of 13 measures cost less than 100 yuan (~\$15.64) per kg of PM_{2.5} emission reduction, including removing small coal-fired boilers, lowering pollution in key industries, controlling road dust, and phasing out outdated industrial capacities. These measures together account for roughly 70% of the existing PM_{2.5} emission reduction capacity. By contrast, the heavily used coal-to-gas and coal-to-power programs were very costly with the highest average abatement cost at 583 yuan/kg (~\$91.20/kg), though these programs brought about significant PM_{2.5} emission reduction in the 2017 HS (Li et al. 2020c; Wang et al. 2020b). After a dramatic cut in PM_{2.5} emissions in 2017 to meet the policy goal stipulated by the Action Plan, there was little room for these measures to further reduce emissions cost-effectively—an inconvenient truth consistent with the PM_{2.5} rebound.

Fig. 6 An average cost curve for PM_{2.5} abatement in China. Data on the abatement effect and average cost of each measure are obtained from Zhang et al. (2019a)

Discussion

Thanks to rigid mitigation measures and favorable meteorological conditions, China has achieved significant reduction in PM_{2.5} concentrations during 2013–2018, especially in northern cities; nevertheless, the post-2018 rebound in PM_{2.5} pollution cannot be overlooked. This study found a PM_{2.5} rebound in northern China in 2019 and early 2020, even though the nationwide PM_{2.5} concentrations remained unchanged from 2018 to 2019. To mitigate the health risk

linked to $PM_{2.5}$ pollution, how to maintain a sustainable $PM_{2.5}$ reduction merits more attention. So, it is necessary to quantify the relative contribution of both anthropogenic and meteorological factors to the $PM_{2.5}$ rebound and link decomposition results to underlying human factors, such as the actual policy readjustment and the increasing marginal cost of mitigation measures.

Our decomposition results differ considerably from the existing study (Yin and Zhang 2020) claiming that meteorological conditions explained 122% of the $PM_{2.5}$ rebound in the 2018 winter and that human factors offset rather than contributed to the $PM_{2.5}$ rebound in the “2 + 26” cities. There may be two explanations for such a qualitative difference. First, we used adjusted $PM_{2.5}$ concentration data to start with, while the previous study did not (see Table 2 for a direct comparison with the literature and the impact of such our data adjustment). The second reason is that different methods were used to fit the observed $PM_{2.5}$ trend: While we applied a stepwise MLR model, the previous study used a chemical transport model (CTM). Though there is no consensus concerning which method performs better, our

model had a better goodness-of-fit. The mean correlation of model fitted values with actual $PM_{2.5}$ concentrations was 0.86 (Fig. 2a; Supplementary Fig. S5), compared to a range of 0.67–0.72 in the previous study based on CTM (Yin and Zhang 2020).

Moreover, our results were generally consistent with those from most previous studies (Table 3). Although few studies investigated the drivers of $PM_{2.5}$ concentrations in post-2018 China, many studies on the previous declining trend of $PM_{2.5}$ suggested that meteorology only played a minor role in the process, regardless of the method being used. For example, a study using MLR indicated that 12% of the $PM_{2.5}$ reduction from 2013 to 2018 was attributable to meteorology (Zhai et al. 2019), while another study used the CTM model and found that meteorology contributed 16% to the reduction from 2013 to 2017 (Zhang et al. 2019b). Thus, it is unreasonable to fully attribute the $PM_{2.5}$ rebound to meteorology while neglecting the anthropogenic factors (Yin and Zhang 2020).

On the methodology front, both MLR and CTM have been widely used to decompose the meteorological and anthropogenic factors behind pollution level changes; however, it is still too early to determine which one is better. While CTM can simulate the chemical process and predict chemical species with more detail (Bey et al. 2001), one limitation of this method is its inherent uncertainty regarding its emission inventory (Chen et al. 2019; Zhong et al. 2021): Even if two studies used the same CTM and focused on the same domain, their decomposition results can vary much (Ding et al. 2019; Dong et al. 2020). By contrast, the uncertainty of the MLR mainly comes from model specifications and its sensitivity to data outliers. Moreover, MLR is unable to provide detailed information on physical and

Table 2 Comparison of mean $PM_{2.5}$ concentrations with and without data adjustment in the winters of 2017 and 2018 for the “2 + 26” cities

	Winter mean (Dec–Feb, $\mu g/m^3$)		
	2017	2018	% change
Yin and Zhang (without adjustment)	71.9	78.7	9.5%
This study (with adjustment)	83.2	95.1	14.3%

Table 3 A summary of meteorological impacts on $PM_{2.5}$ level changes by previous studies

Data source	Domain	Study period	Trends	Method	% meteorology
Yin and Zhang 2020	“2 + 26” cities	2017–2018 winter*	6.80	GEOS-Chem	122.00%
Wang and Zhang 2020a	BTH [†]	2016–2017 winter	−47.70	WRF-Chem	59.90%
Ding et al. 2019	BTH	2013–2017	−30.00	WRF-CMAQ	29.20%
Chen et al. 2020	NCP [‡]	2014–2018	−32.20	MLR	27.00%
Bae et al. 2021	China	2015–2018	−14.30	MLR	27.00%
Zhong et al. 2021	China	2013–2019	−28.90	Two-step method	22.70%
Chen et al. 2019	Beijing	2013–2017	−31.50	WRF-CMAQ	20.00%
Silver et al. 2020	China	2015–2017	−6.80	WFR-Chem	17.60%
Zhang et al. 2019b	China	2013–2017	−19.80	WFR-Chem	16.00%
Cheng et al. 2019	Beijing	2013–2017	−31.50	WRF-CMAQ	12.10%
Zhai et al. 2019	China	2013–2018	−5.20	MLR	12.00%
Dong et al. 2020	BTH	2014–2017	−26.00	WFR-CMAQ	9.00%

*Winter: December to next February

[†]BTH: Beijing-Tianjin-Hebei

[‡]NCP: North China Plain

chemical mechanisms of $PM_{2.5}$ trends as CTM did in previous studies (Wang et al. 2020a; Le et al. 2020; Huang et al. 2021). This, admittedly, is one limitation of our research that merits more future research. Nevertheless, MLR is sufficient to fulfill the main research objective of the paper, i.e., to analyze the long-term trend of $PM_{2.5}$ and decompose the $PM_{2.5}$ rebounds into human and natural factors. Such a statistical approach has been used in other similar research such as Li et al. (2019a) and Zhai et al. (2019). The obtained MLR results can provide useful hints on high-level factors behind the $PM_{2.5}$ rebound and thus help achieve sustainable $PM_{2.5}$ emission reductions.

Broadly speaking, the $PM_{2.5}$ rebound during the heating season characterizes the typical campaign-style governance model of China (Liu et al. 2015; Wang et al. 2021). First is the top-down campaign-style governance with quick and highly visible effects, which may create long-term issues and side effects (Zhao et al. 2020b). Specifically, this model focuses on solving the most-pressing issue with top priorities, at a very quick pace. To solve this problem, the governments set an ambitious goal that needs to be achieved within a limited amount of time and then mobilize and coordinate all types of resources to fulfill that goal. Such a campaign-style model has the merit of taking effect very quickly but cannot sustain the effort due to high costs of implementation. Once the initial goal is reached, the governments will shift their attention and focus to other important issues. This is the case for $PM_{2.5}$ rebound in northern China. The policy goal of a 10% reduction in annual $PM_{2.5}$ from 2012 to 2017 set up by the Action Plan was first over-met by governments leveraging heavy one-size-fits-all measures regardless of their relative cost-effectiveness (Zhang et al. 2019b). However, this was later followed by a rebounding effect of as high as 65% in the following heating seasons for northern cities in China.

Given the increasing marginal costs of emission reductions (Fig. 6), we do not believe that the Chinese government intended to adjust the goals and measures to result in the $PM_{2.5}$ rebounds, but only the result of a dynamic process characterized by the campaign-style governance model. In other words, the $PM_{2.5}$ rebound we found for northern cities only followed after deep cuts in $PM_{2.5}$ concentrations previously. It is interesting to note that the magnitude of and the reasons for the $PM_{2.5}$ rebounds in “2+26” cities and other northern cities was somewhat different. Specifically, the rebounding effect in “2+26” cities was greater than that of other northern cities in the 2018 HS. This is because “2+26” cities were chosen as the targeted region in the annual action plan since 2017 and thus had to reduce $PM_{2.5}$ pollution more seriously in the 2017 HS. Owing to the policy re-adjustment and increasing marginal costs later on, $PM_{2.5}$ concentrations in “2+26” cities rebounded more in the 2018 HS than in other northern

cities. If without the previous deeper cuts in $PM_{2.5}$ concentrations, we should not expect “2+26” cities to perform worse than other cities in terms of either $PM_{2.5}$ mitigation or $PM_{2.5}$ rebounds. Such a comparison between “2+26” and other northern cities suggests that China’s campaign-style governance model had its spatial range limitations. Furthermore, the campaign on $PM_{2.5}$ also produced other repercussions. Studies found that southern cities experienced natural gas shortages owing to the hyped coal-to-gas program in the north and these cities had to revert to coal for production and heating (Wang et al. 2020b). The decrease in $PM_{2.5}$ concentrations in northern China even contributed to the increase in O_3 concentrations in the summer owing to the excessive attention on $PM_{2.5}$ controls (Li et al. 2019b; Wang et al. 2020c; Zhao et al. 2020a).

Second is the system’s ability to adapt to emerging problems and new situations in the process. In the case of controlling China’s $PM_{2.5}$ pollution, the re-adjustment of policy targets and the insertion of flexibilities into policy measures after 2017 may reflect certain degrees of self-learning and system re-calibration, rather than pure rebounding. After all, the rising abatement cost and potential GDP loss (Li et al. 2019c) cannot simply be ignored and must be carefully balanced with $PM_{2.5}$ emission reduction. The end result is that even considering the relaxation of policy stringency and the rebound effect, China’s overall speed in reducing $PM_{2.5}$ concentrations is still faster than that of its counterparts from the developed world (Greenstone et al. 2021). Similar findings also exist in relation to China’s reduction of its coal overcapacity (Dong et al. 2021). Whether a smooth or curly path can better address these complex collective action problems deserves more attention and fundamental research.

In sum, the main contribution of this paper is to confirm the $PM_{2.5}$ rebound in northern China from Nov 2018 to Jan 2020. After decomposing the changes in $PM_{2.5}$ concentrations via a statistical approach, this study highlights the important role played by human factors, in particular the policy re-adjustment and the increasing marginal costs of $PM_{2.5}$ abatement. However, there are still some data and methodological limitations that need to be addressed in future research. First, though the statistical approach was straightforward, it was unable to offer detailed information about the contribution of different mitigation measures. Future studies could collect more data and quantify the relative contributions of those different measures to the $PM_{2.5}$ rebound. Second, due to the COVID-19 lockdown, the statistical approach could not separate its confounding effect on $PM_{2.5}$ from the other non-COVID-related human factors that we care about. More future work should be done to control for confounding factors such as COVID-19 in order to examine more recent trends of $PM_{2.5}$. Lastly, it would also be interesting to compare the relative performance of

our statistical approach and chemical transport modeling approach with more data inputs and more research efforts in the future.

Conclusion and policy implications

This study found that mean $PM_{2.5}$ concentrations in northern China continued to decline from 2015 to 2018. However, the $PM_{2.5}$ pollution in this heavily polluted region has rebounded in 2019 and early 2020 before COVID-19, mostly due to changes during the heating season. Furthermore, anthropogenic factors have contributed roughly 50% of the rebound on average to this rebound after contributing to a severe cut of $PM_{2.5}$ emissions in 2017. The underlying reasons for this $PM_{2.5}$ rebound and the contribution from human factors have a lot to do with the systemic re-adjustment of policy targets and mitigation measures by the central government, as well as the rising abatement cost of many mitigation measures, rather than mere meteorological factors. In other words, such a human-induced $PM_{2.5}$ rebound is the result of a dynamic process under the campaign-style governance model.

Regardless of the merits or demerits of China's governance model, successfully addressing $PM_{2.5}$ pollution brings about substantial environmental and human health benefits, as well as co-benefits for climate change. Challenges, however, still exist concerning how to maintain the previous efforts and momentums, potentially in a smarter and more cost-effective way. Based on our results and discussion, we make the following policy recommendations. First, chart a more sustainable path for future $PM_{2.5}$ emission reductions to meet the 2035 policy target of $35 \mu\text{g}/\text{m}^3$ while avoiding possible rebounding effects. This includes paying more attention to key cities and key polluting seasons, both in the north and south, while not only focusing on the national annual mean concentration levels. Second, dynamically adjust the portfolio of mitigation measures based on their relative cost-effectiveness and social acceptance, strike a good balance between policy stringency and flexibility, and differentiate the contributions from natural and human factors. Third, address $PM_{2.5}$ pollution together with other energy and environmental issues, leverage system synergies and co-benefits, and employ a multi-goal governance system.

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Availability of data and materials The dataset with adjusted $PM_{2.5}$ concentrations is available from GitHub (https://github.com/rosenbloog/China_pm2.5).

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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