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Hospital admissions attributable to reduced air pollution due to clean-air policies in China

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The Air Pollution Prevention and Control Action Plan (APPCAP) is considered to be the most stringent air pollution control policy in China implemented since 2013. This policy is a milestone in China to mitigate serious air pollution. However, health benefits attributable to reduced fine-particulate air pollution after the implementation of the APPCAP have not been quantitatively estimated on a $PM_{2.5}$ constituent-specific and morbidity cause-specific basis. Here we conducted a nationwide case-crossover study based on hospital admission records in 292 Chinese cities during 2013-2017. Compared with 2013, the annual average concentrations of $PM_{2.5}$ and black carbon (BC) in 2017 decreased by 28.61% and 20.35%, respectively. As a result, the average relative reductions in annual attributable fractions of nine major cause-specific hospital admissions associated with $PM_{2.5}$ and BC were 30.00% and 21.14%, respectively, among which annual attributable fraction for depression showed the largest reduction. Nationally, cities with higher reductions in $PM_{2.5}$ and BC were found to have higher absolute reductions in annual hospital admission attributable fractions associated with $PM_{2.5}$ and BC, and geographic inequality in health benefits still existed. Our study highlights the substantial wide-ranging health benefits of reduced $PM_{2.5}$ and BC levels following the nationwide implementation of the APPCAP in China.

To date, ambient particulate matter remains a major contributor to global disease burden. Strong evidence has linked exposure to particulate matter with an aerodynamic diameter of 2.5 µm or less ($PM_{2.5}$) pollution to an array of adverse health outcomes, including mortality or morbidity of respiratory disease[1], cardiovascular disease (CVD)[2] and mental health conditions[3]. In particular, short-term exposure to $PM_{2.5}$ has been found to trigger the onset of disease episodes such as cardiovascular events and psychiatric symptom episodes, which may request subsequent hospital admissions for intensive treatment[4,5]. Compared with mortality, morbidity risk measured by hospital admission may serve as a more sensitive health indicator to capture the acute health effects of environmental exposures[5–7].

With the rapid economic growth and urban development over the three decades from the 1980s to the 2000s, China has experienced severe fine-particulate air pollution[8]. To mitigate fine-particulate air pollution levels and related health impacts, the State Council of China introduced the Air Pollution Prevention and Control Action Plan (APPCAP) in 2013. This plan introduced ten specific measures spanning industrial emissions control, clean energy promotion, vehicle emission standards improvements, air-quality monitoring systems optimization and tax

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and cap-and-trade policies support[9,10]. The APPCAP is a nationwide plan involving multiple sectors, industries and governmental levels and sets binding targets for air-quality improvement achieved in 2017[10]. The unique aspects of the APPCAP in China lie in its holistic approach to air pollution control, making it effective in achieving substantial declines in air pollution in such a relatively short period of 5 years[11]. It is estimated that compared with 2013, the annual average concentrations of $PM_{2.5}$ in 2017 decreased by 33.3% in 74 key Chinese cities[12]. In contrast, similar air-quality improvements were usually obtained over a longer period in other countries attempting to improve air quality. For example, it is estimated that the Clean Air Act in the United States (US) would reduce the national annual $PM_{2.5}$ concentrations by 41% over the period between 1990 and 2020[13]. Similarly, annual average concentrations of $PM_{2.5}$ and black carbon (BC) in 2010 were 35% and 56% lower compared to emissions that would have occurred in 2010 without legislative and technological measures implemented in Europe since the 1970s[14].

Quantifying the health benefits associated with air pollution control actions not only evaluates the impact of current policies but also provides insights for formulating future strategies. Air pollution control actions around the world have achieved substantial health benefits for multiple health indicators, including years of life lost[12], gain of life expectancy[15,16] and premature mortality[17,18]. It is estimated that the implementation of the APPCAP in China contributed to about 55,000 fewer premature deaths in 2017 compared to 2013 in 74 key Chinese cities[12], and the reduced $PM_{2.5}$ pollution from 2013 to 2017 contributed to 64,000 fewer deaths nationwide[19]. However, the current studies are mainly restricted to specific regions[20–23]. Meanwhile, the health benefits of reduction in $PM_{2.5}$ were primarily evaluated by risk assessment based on extrapolating previously published exposure-response relationships obtained from other populations beyond the populations being investigated, such as integrated exposure-response functions used in the Global Burden of Disease studies[24], which may overexpand the representativeness of the exposure-response relationships and result in biased estimates of the corresponding health benefits.

As a mixture, the major constituents of $PM_{2.5}$ include carbonaceous fractions such as BC and organic matter (OM), and water-soluble inorganic ions such as sulfate, nitrate, ammonium and chloride[25]. The key $PM_{2.5}$ constituents driving the disease risk and burden related to $PM_{2.5}$ are still inconclusive based on the existing studies[26–30]. Therefore, the existing epidemiological evidence remains insufficient to establish the air-quality guidelines for specific $PM_{2.5}$ constituents. Instead, the World Health Organization (WHO) has only published a good practice statement for BC or elemental carbon and appealed for further evidence[31]. Pollution due to ambient $PM_{2.5}$ and its major constituents remains a serious and continuing environmental challenge, and detailed estimation of health benefits attributable to reductions in $PM_{2.5}$ and its constituents based on real-world exposure-response relationships over a wide geographical area is needed to evaluate the efficiency of the massive air pollution control actions[32]. Furthermore, identifying the key $PM_{2.5}$ constituents of which reduction would bring more substantial health benefits to the general population could provide evidence to inform source control strategies, targeted air-quality guidelines formulation and disease prevention practices in the future.

In this study, by conducting a nationwide case-crossover analysis, we aimed to quantify the health benefits attributable to the reduced fine-particulate air pollution after the implementation of the APPCAP during 2013-2017 based on the exposure-response relationships between short-term exposure to fine-particulate air pollution and hospital admissions for ten major diseases and their respective subtypes. Table 1 summarizes our findings and policy implications.

Results

Changes in $PM_{2.5}$ and its constituents over time

During 2013-2017, the national average pollution levels were 48.20 μg/m^3 for $PM_{2.5}$, 2.81 μg/m^3 for BC, 10.39 μg/m^3 for sulfate, 8.25 μg/m^3 for nitrate, 6.15 μg/m^3 for ammonium, 2.09 μg/m^3 for chloride and 18.52 μg/m^3 for OM (Supplementary Table 1). Geographically, heavy fine-particulate air pollution was found in cities located in North China, Central China, East China and Sichuan Basin during the study period. Heavy air pollution was also observed in cities located in southwest Xinjiang Uygur Autonomous Region (Extended Data Fig. 1). As shown in Fig. 1, the annual absolute declining rates of $PM_{2.5}$ and its major constituents were apparent in all included cities. Specifically, greater declines in air pollution were mainly observed in cities located in North China, Central China, East China and Sichuan Basin over the period of 2013-2017. The declining rates were much smaller in cities located in Northwest China, Northeast China, South China, and North China nearing the Mongolian border. Nationally, the annual absolute declining rates weres 4.23 μg/m^3 per year for $PM_{2.5}$ and 0.17 μg/m^3 per year for BC. Compared with 2013, we observed reductions of 16.32 μg/m^3 (28.61%) for $PM_{2.5}$, 0.65 μg/m^3 (20.35%) for BC, 2.89 μg/m^3 (24.43%) for sulfate, 2.36 μg/m^3 (24.80%) for nitrate, 1.60 μg/m^3 (22.90%) for ammonium, 0.51 μg/m^3 (21.79%) for chloride and 8.32 μg/m^3 (35.85%) for OM in 2017 across the included cities (Extended Data Fig. 2).

Major $PM_{2.5}$ constituents and hospital admissions

A total of 48,623,468 cause-specific hospital admission records in 292 Chinese cities of prefecture level or above during 2013-2017 were included in this analysis. To provide exposure-response relationships for further calculation of hospital admission attributable fractions and align with the primary aim of health benefits assessment, we evaluated the percent changes in cause-specific hospital admission risks for each interquartile range (IQR) increase in $PM_{2.5}$ and its major constituents. We observed statistically significant positive associations between short-term exposures to $PM_{2.5}$ and its major constituents with various cause-specific hospital admissions, except for asthma, acute bronchiolitis, hemorrhagic stroke, chronic nephritis and hypertensive kidney disease (Supplementary Table 2). Among the major $PM_{2.5}$ constituents, BC was recognized as the key constituent associated with higher risks in hospital admissions for different disease subtypes, ranging from 1.20 times higher percent change in admissions for diabetic kidney disease to 1.96 times higher percent change in admissions for coronary heart disease (CHD) compared with the percent changes associated with $PM_{2.5}$ at the scale of per IQR increase. As shown in Supplementary Tables 3–5, the constituent residual model and the remaining $PM_{2.5}$ mass-adjusted model verified the independent associations between BC and major cause-specific hospital admissions (all corrected P values < 0.05). In the two-constituent model, the associations between BC and cause-specific hospital admissions remained consistent after adjusting for the other major constituents (sulfate, nitrate, ammonium, chloride and OM) separately, whereas there were no associations observed between the other major constituents and cause-specific hospital admissions after adjusting for BC (Extended Data Fig. 3). These results verified the independent associations of BC with cause-specific hospital admissions. Thus, we identified BC as the key major $PM_{2.5}$ constituent and further quantified the health benefits attributable to $PM_{2.5}$ and BC reductions.

As shown in Supplementary Table 6, the associations between BC at lag01 (referred to the 2-day moving average air pollution concentrations of the present day and previous day) and cause-specific hospital admissions showed no significant differences between cities with a majority of urban residents versus cities with a majority of rural residents, except for lower respiratory infections and chronic kidney disease (CKD). Several sensitivity analyses which included changing the lag period of air pollutants, changing the lag period of temperature and relative humidity, restricting analyses to cities with 5-year hospital admission data, adjusting for time spline for day of the year and conducting the case-crossover analysis based on symmetric bidirectional matching strategy within a narrower window of 14 days, confirmed the robustness of the main results (Supplementary Tables 7–9).

Table 1 | Policy summary

Background	With rapid economic growth, fine-particulate air pollution has become one of the most pressing and severe environmental challenges in China over the three decades from the 1980s to the 2000s. In 2013, the State Council of China issued the APPCAP, the most stringent air pollution control policy in China, to mitigate heavy air pollution and related health burdens. The APPCAP comprised ten specific tasks and established reachable specific air-quality improvement targets. Compared to air pollution control policies in other countries, setting feasible targets, categorizing key regions and implementing a holistic approach involving multiple sectors, industries and governmental levels made the APPCAP effective in achieving substantial declines in air pollution within a relatively short period of only 5 years. To date, little research has quantified the health benefits attributable to reduced air pollution due to clean-air policies in China on a $PM_{2.5}$ constituent-specific and morbidity cause-specific basis in a real-world scenario.
Main findings and limitations	Using nationwide hospital admission data from two major national medical insurance systems in China, we observed that reduced fine-particulate air pollution after the implementation of the APPCAP was accompanied by wide-ranging health benefits, reflected by substantial reductions in attributable fraction of hospital admissions for major respiratory, cardiovascular, mental, neurological, and kidney diseases, of which hospital admission for depression was found to benefit most from the reduced air pollution. The average relative reductions in annual attributable fractions of nine major cause-specific hospital admissions associated with $PM_{2.5}$ and BC were 30.00% and 21.14% from 2013 to 2017, respectively. Nationally, city-specific annual attributable fractions decreased significantly along with absolute reductions in $PM_{2.5}$ and BC during 2013-2017. Compared with $PM_{2.5}$, the cumulative reduction in BC could avoid more cause-specific hospital admissions during 2014-2017 compared with 2013. However, geographic inequality in health benefits still existed. Limitations of this study included the unavailability of health data after 2017 and the inability to distinguish first-time admissions and readmissions or obtain individual-level information.
Policy implications	Our findings imply that clean-air policies in China have brought substantial health benefits attributable to reduced air pollution at the nationwide level, whereas regional inequality still exists. Precision air pollution control strategies with consideration of regional heterogeneity are recommended in future policy-making. Our results also highlight that BC may be the leading $PM_{2.5}$ constituent that could be considered as a potential priority constituent in future air pollution control actions in order to obtain more substantial health benefits.

Attributable fraction declines due to reduced air pollution

As statistically significant associations between air pollution and hospital admission for asthma were not observed, we did not include asthma in subsequent analyses of attributable fractions. As shown in Fig. 2 (detailed data are shown in Supplementary Tables 10 and 11), the annual attributable fractions of nine major cause-specific hospital admissions (including lower respiratory infections, cardiac arrhythmias, CHD, heart failure, stroke, depression, schizophrenia, Parkinson's disease and CKD) associated with short-term exposures to $PM_{2.5}$ and BC declined substantially after the implementation of the APPCAP during 2013-2017. Specifically, we observed an average of 1.34% absolute reduction in nine major cause-specific hospital admissions attributable to BC (ranging from 0.87% for heart failure to 2.67% for depression) from 2013 to 2017, higher than the average absolute reduction of 1.08% (ranging from 0.73% for heart failure to 2.00% for depression) attributable to $PM_{2.5}$ from 2013 to 2017. The corresponding average relative reduction in annual attributable fractions in nine major cause-specific hospital admissions from 2013 to 2017 associated with BC was 21.14%, ranging from 17.76% for Parkinson's disease to 27.01% for low respiratory infections. This fraction was 30.00% associated with $PM_{2.5}$, ranging from 24.53% for CKD to 34.35% for depression. The Theil-Sen median slope estimator showed that the annual absolute declining rates of attributable fractions for major cause-specific hospital admissions associated with $PM_{2.5}$ ranged from 0.20% per year for CHD to 0.52% per year for depression. Larger annual absolute declining rates were observed for BC, ranging from 0.24% per year for heart failure to 0.74% per year for depression (Table 2).

In the sensitivity analyses restricted to cities with 5-year data on hospital admissions, an average absolute reduction of 1.02% and an average relative reduction of 30.80% in the annual attributable fractions of nine major cause-specific hospital admissions associated with $PM_{2.5}$ from 2013 to 2017 were observed (Supplementary Table 12), and an average absolute reduction of 1.20% and an average relative reduction of 20.97% in the annual attributable fractions of nine major cause-specific hospital admissions associated with BC from 2013 to 2017 were observed (Supplementary Table 13).

Avoided hospital admissions due to reduced air pollution

Compared with 2013, the cumulative $PM_{2.5}$ reduction during 2014-2017 after the implementation of the APPCAP was estimated to have avoided a total of 271,984 (95% confidence interval (CI), 180,144–364,065) hospital admissions for the nine major diseases, ranging from 2,199 (95% CI, 978–3,426) hospital admissions for Parkinson's disease to 109,478 (95% CI, 73,531–145,512) hospital admissions for low respiratory infections. Meanwhile, the estimated total avoided number was 322,968 (95% CI, 243,861–402,253), ranging from 2,309 (95% CI, 1,262–3,361) hospital admissions for Parkinson's disease to 123,329 (95% CI, 93,364–153,354) hospital admissions for low respiratory infections, for the cumulative BC reduction during 2014-2017 in the 292 cities being included. Lower respiratory infections, CHD and stroke were the three leading diseases with the highest avoided admission numbers associated with reductions in $PM_{2.5}$ and BC (Fig. 3).

Regional health benefits of reduced air pollution

Spatial distributions of health benefits and reductions in fine-particulate air pollution between 2013 and 2017 are presented in Fig. 4. More substantial health benefits associated with reduced $PM_{2.5}$ and BC were observed in North China, East China and Sichuan Basin, where fine-particulate air pollution was reduced more substantially in these regions during the study period.

City-specific absolute reductions in annual hospital admission attributable fraction were well correlated with city-specific absolute reductions in $PM_{2.5}$ (Extended Data Fig. 4) and BC (Extended Data Fig. 5) at the nationwide level. However, there were some outlier cities: 11 cities (5 located in Central China) showed large reductions in annual hospital admission attributable fraction but modest reductions in $PM_{2.5}$, 28 cities (ten located in Northwest China) showed increases in annual hospital admission attributable fraction despite reductions in $PM_{2.5}$ during the study period and 1 city (located in North China) showed a large reduction in $PM_{2.5}$ but a small reduction in annual hospital admission attributable fraction. As for BC, the numbers of the above three types of outlier cites were 9 (5 located in Central China), 29 (12 located in Northwest China) and 1 (located in Central China), respectively. The scatter plots for city-specific absolute reductions in $PM_{2.5}$ versus absolute reductions in annual attributable fraction showed that the magnitude of city-specific absolute reductions in annual attributable fraction appeared to significantly increase along with larger reductions in $PM_{2.5}$ in cities located in North China, Northeast China, East China and Southwest China (including Sichuan Basin). In contrast, for cities located in Central China, Northwest China and South China, the magnitude of absolute reductions in annual attributable fraction

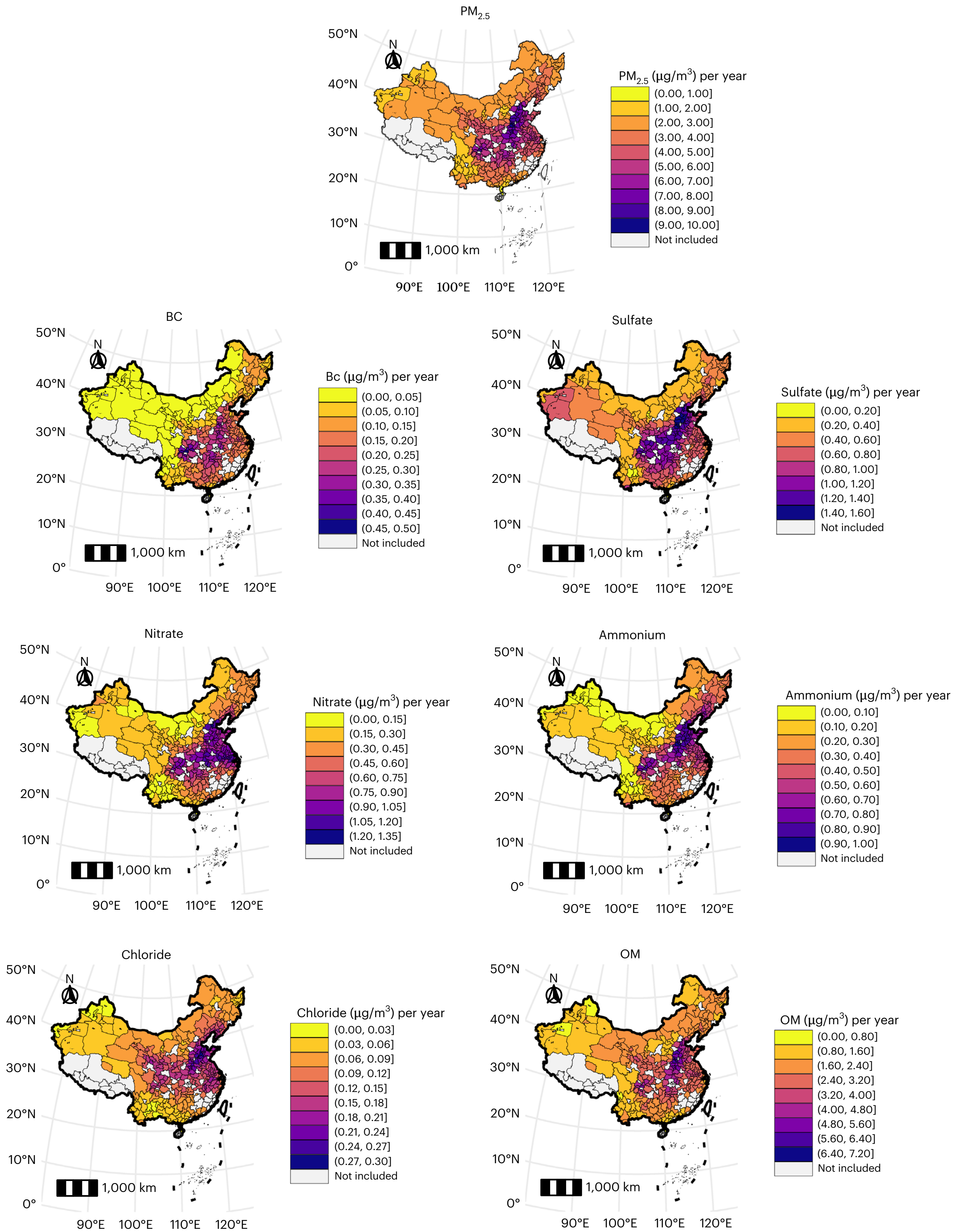

Fig. 1 | Spatial distribution of city-specific annual absolute declining rates of ambient $PM_{2.5}$ and its major constituents in 292 Chinese cities of prefecture level or above during 2013-2017. City-specific annual absolute declining rates in ambient $PM_{2.5}$ and its major constituents were estimated by the Theil-Sen median slope estimator (presented in micrograms per cubic meter per year). Deeper color presents a larger decline per year. Cities in gray were not included in the analyses because no hospital admission data were available during the study period.

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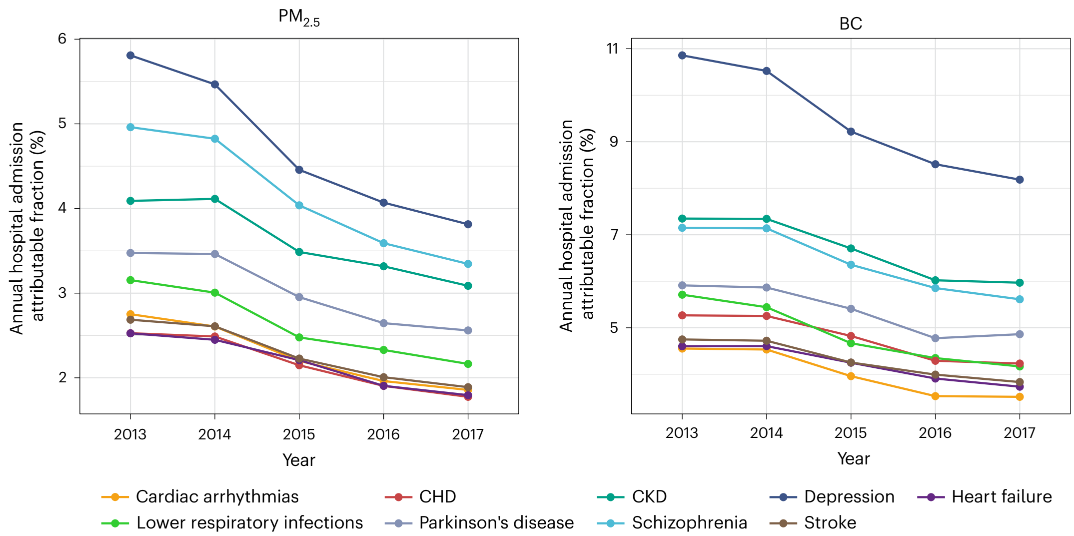

Fig. 2 | Annual attributable fractions of major cause-specific hospital admissions associated with ambient $PM_{2.5}$ and BC at lag01 in 292 Chinese cities of prefecture level or above during 2013-2017. The annual attributable fractions for cause-specific hospital admissions were calculated based on the exposure-response relationships with a theoretical minimal risk exposure level of 0 μg/m^3 as the reference concentration. Annual attributable fractions of hospital admissions for asthma were not included in the figure because of the insignificant associations with $PM_{2.5}$ and BC. Annual attributable fractions of major cause-specific hospital admissions were calculated based on relative risks generated from the basic single-constituent model and were calculated for cities with hospital admission data in that year. Each dot represents a point estimate of the annual attributable fraction. Each line connecting the points presents the trend of annual attributable hospital admission fractions associated with ambient $PM_{2.5}$ and BC.

Table 2 | Reductions in annual attributable fractions of major cause-specific hospital admissions associated with ambient $PM_{2.5}$ and BC at lag01 in 292 Chinese cities of prefecture level or above in 2017 compared with 2013[a,b]

Cause-specific hospital admission[c]	$PM_{2.5}$			BC		
	Absolute reduction (%)[d]	Relative reduction (%)[e]	Annual absolute declining rate (% per year)[f]	Absolute reduction (%)[d]	Relative reduction (%)[e]	Annual absolute declining rate (% per year)[f]
Lower respiratory infections	0.99 (0.67, 1.30)	31.39 (31.23, 31.55)	**0.26**	1.54 (1.19, 1.88)	27.01 (26.82, 27.20)	**0.41**
Cardiac arrhythmias	0.89 (0.51, 1.27)	32.52 (32.33, 32.72)	**0.24**	1.04 (0.69, 1.37)	22.79 (22.62, 22.98)	**0.32**
CHD	0.75 (0.50, 1.00)	29.74 (29.62, 29.87)	**0.20**	1.04 (0.83, 1.24)	19.67 (19.57, 19.78)	**0.31**
Heart failure	0.73 (0.33, 1.12)	28.92 (28.73, 29.11)	**0.21**	0.87 (0.53, 1.19)	18.90 (18.72, 19.08)	0.24
Stroke	0.80 (0.57, 1.02)	29.66 (29.55, 29.77)	**0.22**	0.92 (0.72, 1.10)	19.29 (19.19, 19.40)	**0.25**
Depression	2.00 (0.81, 3.09)	34.35 (33.81, 34.89)	**0.52**	2.67 (1.59, 3.63)	24.61 (24.03, 25.20)	**0.74**
Schizophrenia	1.62 (1.04, 2.17)	32.56 (32.29, 32.83)	**0.45**	1.54 (1.05, 2.00)	21.50 (21.25, 21.74)	**0.41**
Parkinson's disease	0.91 (0.42, 1.39)	26.33 (26.06, 26.60)	**0.27**	1.05 (0.59, 1.48)	17.76 (17.51, 18.01)	0.30
CKD	1.00 (0.72, 1.28)	24.53 (24.37, 24.69)	0.25	1.38 (1.08, 1.67)	18.77 (18.57, 18.97)	**0.41**
Average	1.08 (0.62, 1.52)	30.00 (29.78, 30.23)	**0.29**	1.34 (0.92, 1.73)	21.14 (20.92, 21.37)	**0.38**

[a]The attributable fractions for cause-specific hospital admissions were calculated based on the exposure-response relationships with a theoretical minimal risk exposure level of 0 μg/m^3 as the reference concentration. [b]Annual attributable fractions were calculated for cities with hospital admission data in that year. [c]Reductions in annual attributable fraction of hospital admissions for asthma were not shown because of the insignificant associations between $PM_{2.5}$ and BC and admissions for asthma in the single-constituent model. [d]Compared with the annual hospital admission attributable fraction in 2013, the absolute reduction in annual hospital admission attributable fraction in 2017 was calculated by subtracting the annual hospital admission attributable fraction in 2017 from the annual attributable fraction in 2013. [e]Compared with the annual hospital admission attributable fraction in 2013, the relative reduction was calculated by dividing the absolute reduction in annual attributable fraction in 2017 (with reference to the annual attributable fraction in 2013) by the annual attributable fraction in 2013. [f]The Theil-Sen median slope estimator along with the Mann-Kendall test was used to quantify the strength of the annual absolute declining rate and its statistical significance. Estimates with $P < 0.05$ (two sided) are marked in bold.

did not show increasing trends along with larger reductions in $PM_{2.5}$. In contrast to $PM_{2.5}$, for cities located in Northwest China, absolute reductions in annual attributable fraction were positively associated with absolute reductions in BC.

Concerning the impact of city urbanization rate, the average relative reduction in annual attributable fractions across major cause-specific hospital admissions associated with $PM_{2.5}$ in 2017 was 31.72% (for nine major diseases) in cities with a majority of urban residents, compared with 2013, whereas this fraction was 23.90% (for seven major diseases, with the exception of Parkinson's disease and depression because of statistically insignificant subgroup associations) in cities with a majority of rural residents.

Discussion

In this study, we quantified the health benefits attributable to reduced fine-particulate air pollution on a $PM_{2.5}$ constituent-specific and morbidity cause-specific basis after the implementation of the APPCAP in China. Aligning with the declines in fine-particulate air pollution

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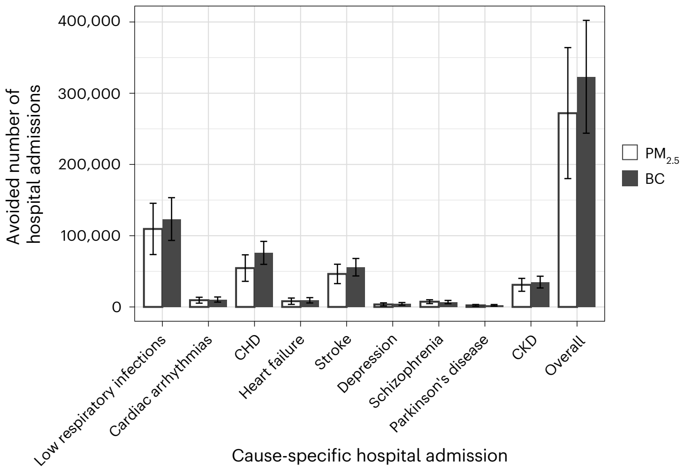

Fig. 3 | Total avoided numbers of cause-specific hospital admissions attributable to cumulative reductions in ambient $PM_{2.5}$ and BC in 292 Chinese cities of prefecture level or above during 2014-2017 compared with 2013. Supplementary Table 15 shows the summary admission numbers for different cause-specific hospital admissions during the study period. Overall, $n = 48{,}623{,}468$. Error bars represent 95% CIs. Each line connecting the error bars illustrates the range of avoided number of cause-specific hospital admissions attributable to the cumulative reduction in $PM_{2.5}$ or BC during 2014-2017 compared with 2013.

levels from 2013 to 2017, we observed substantial reductions in annual attributable fractions for nine major cause-specific hospital admissions associated with $PM_{2.5}$ and BC. Geographically, cities with higher reductions in $PM_{2.5}$ and BC showed higher absolute reductions in annual attributable fractions associated with $PM_{2.5}$ and BC, especially in North China, East China and Sichuan Basin. Additionally, compared with the cumulative $PM_{2.5}$ reduction during 2014-2017 after the implementation of the APPCAP, cumulative BC reduction could avoid more cause-specific hospital admissions. Taken together, the APPCAP effectively reduced fine-particulate air pollution and brought substantial health benefits within a relatively short period of 5 years. In addition, BC may be the potential key major $PM_{2.5}$ constituent of which reduction would bring more substantial health benefits.

Such health benefits associated with air-quality improvements have also been identified in Western developed countries over longer historical periods. Implementation of amendments to the Clean Air Act in the US was estimated to avoid approximately 15,000 hospital admissions for dementia and 15,000 to 25,000 hospital admissions for CVD each year between 1990 and 2000 (ref. 33), and more than 160,000 premature deaths and 86,000 all-cause hospital admissions in 2011 compared with counterfactual no implementation scenario[34]. Air pollution mitigation measures were implemented much earlier in Europe (since the 1970s), and such reductions in $PM_{2.5}$ were estimated to prevent more than 80,000 premature deaths annually, which was 19% of the estimated premature deaths due to absolute $PM_{2.5}$ concentrations in 2011 across Europe[14]. Analogous to the Clean Air Act in the US and air pollution mitigation measures in Europe, the implementation of the APPCAP in China represents a milestone in achieving reductions in air pollution-associated health burdens. Notably, the APPCAP in China gained substantial health benefits within only 5 years, whereas it took decades longer for other air pollution mitigation campaigns in the US and Europe.

We observed that the magnitude of reduced attributable fractions in hospital admissions varied in different geographical regions. Specifically, larger reductions in annual attributable fraction were observed in cities located in several key regions, including North China, East China and Sichuan Basin, which were correlated with larger reductions in fine-particulate air pollution over the study period. Great efforts were taken to combat severe air pollution in these areas, including optimizing industrial structures, accelerating technological upgrades and promoting the use of clean energy to meet the established targets[10]. As a consequence, substantially improved air quality and associated health benefits were observed in these key regions[35].

However, we also observed uneven geographical distribution of health benefits associated with air pollution reduction, which may be attributable to different socioeconomic characteristics (such as urbanization and medical accessibility), different levels of region-specific air pollution control targets, different natural conditions (such as terrain effects and climate) and different regional pollution profiles[16,36,37]. In some cities, absolute reductions in annual attributable fraction did not reflect changes in air pollution, which is similar to a previous analysis on provincial average gain in life expectancy in association with changes in $PM_{2.5}$ from 2013 to 2017[16]. For example, in several cities located in South China, the annual attributable fractions slightly declined or even increased along with small reductions in $PM_{2.5}$ from 2013 to 2017. This may be because $PM_{2.5}$ concentrations in cities located in South China were relatively low in 2013 and the decreases in $PM_{2.5}$ concentrations (from an average of 42.13 μg/m^3 in 2013 to an average of 31.67 μg/m^3 in 2017) over the study period were modest and may not be able to generate substantial health benefits. In addition, several cities located in Central China were recognized as outliers, and we did not observe appreciable health benefits along with reductions in $PM_{2.5}$ and BC in this region. One potential reason is that Central China was not recognized as a key region for air pollution control actions and did not set a clear air pollution control target during the implementation of the APPCAP[37]. For several cities located in Northwest China, city-specific annual attributable fractions increased from 2013 to 2017 despite reductions in $PM_{2.5}$ during the study period, which is similar to a previous study that found decreased gain in life expectancy in association with clean-air policies during 2013-2017 in Northwest China[16]. These results suggest that future clean-air policies should focus not only on reducing the average concentration of air pollution but also on minimizing geographic inequality caused by regional differences in air pollution mitigation.

The estimated declines of annual attributable fractions over the study period were more apparent between 2014 and 2015. This difference may be because more stringent control measures were implemented in the first 3 years of the APPCAP[38]. However, new challenges appeared afterward, such as the increased complexity of industrial restructuring, which reduced the speed of air-quality improvements in the later years of the study[39]. This implies that the policies and actions need to evolve to address new and emerging challenges effectively.

For other countries facing severe air pollution challenges, the APPCAP provides several lessons from China's experience in air pollution control and disease prevention practices. First, the APPCAP represents shifts in development strategy through prioritizing a transition from a sole focus on economic growth to emphasizing both environmental and economic sustainability. Second, the APPCAP is a centralized, government-led initiative with multisector engagement. This ensures that air pollution control efforts are driven by strong government leadership while involving multiple sectors for a coordinated approach. Third, the APPCAP involves the adoption and development of technologies to enhance monitoring systems and implement robust early warning mechanisms.

To date, evidence for the leading constituents in $PM_{2.5}$ has been inconclusive[28,40–42], possibly because $PM_{2.5}$ constituents vary over time and space, which may lead to differential toxicity of $PM_{2.5}$ (ref. 43). Additionally, previous studies were mostly regional (limited to several specific cities) and mainly focused on risks of mortality rather than morbidity. Few studies have evaluated the health benefits of reduced fine-particulate air pollution at the constituent-specific level; instead, our study provides evidence on the health benefits of key $PM_{2.5}$ constituents at the nationwide level. We observed that BC reduction could

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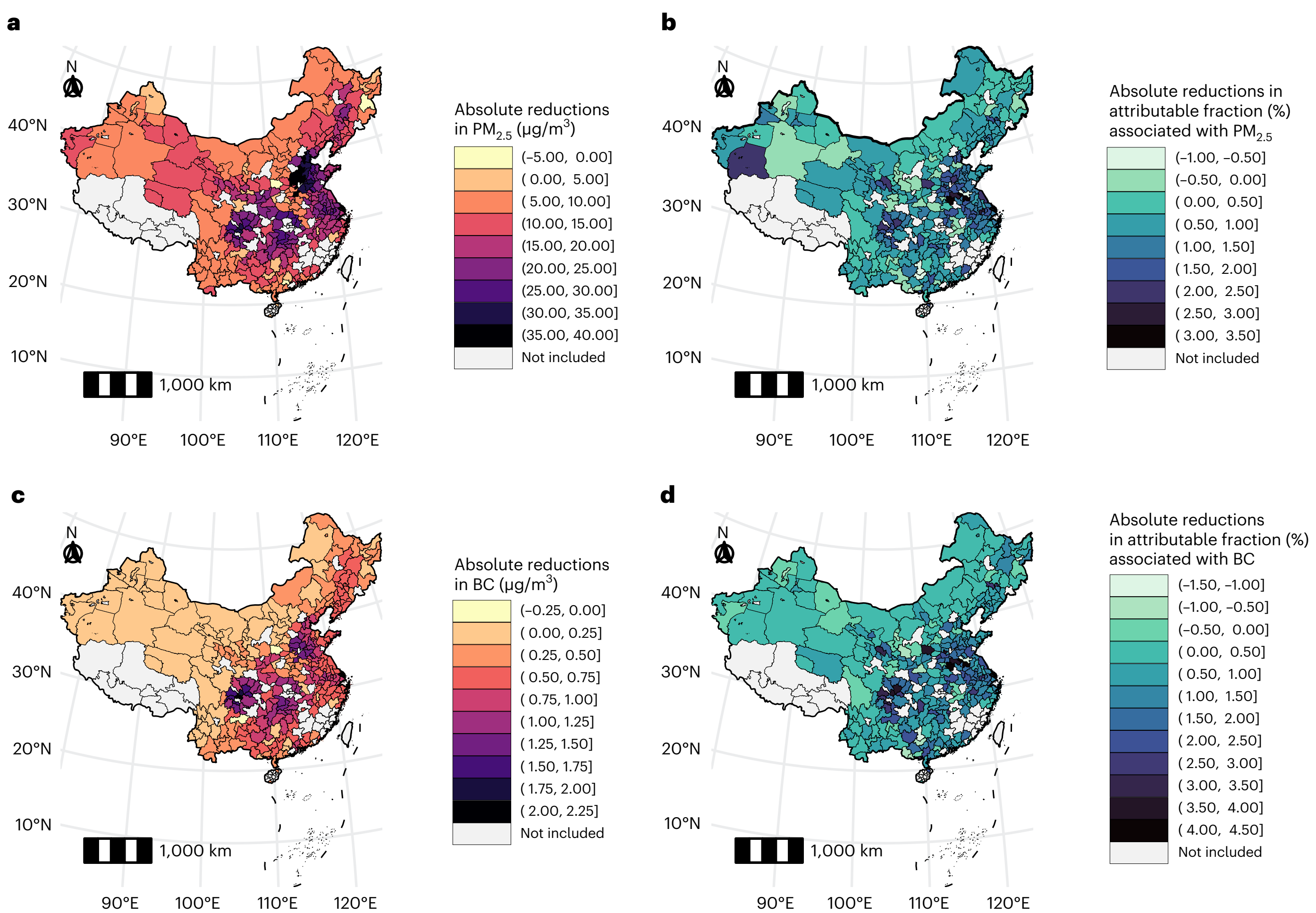

Fig. 4 | Spatial distribution of city-specific absolute reductions in annual average concentrations of ambient $PM_{2.5}$ and BC and average annual hospital admission attributable fractions of nine major cause-specific hospital admissions associated with ambient $PM_{2.5}$ and BC in 292 Chinese cities of prefecture level or above in 2017 compared with 2013. a,**c**, Spatial distribution of city-specific absolute reductions in annual average concentrations of ambient $PM_{2.5}$ (**a**) and BC (**c**). **b**,**d**, Spatial distribution of city-specific absolute reductions in annual hospital admission attributable fractions associated with ambient $PM_{2.5}$ (**b**) and BC (**d**). City-specific annual attributable fractions were averaged for nine major cause-specific hospital admissions with significant associations with $PM_{2.5}$ and BC. Absolute reduction in annual attributable fraction was calculated by subtracting the annual attributable fraction in 2017 from the annual attributable fraction in 2013 for each city. For cities with data fewer than 5 years (the number of cities with data fewer than 5 years ranged from 54 for depression to 87 for heart failure), absolute reductions in annual attributable fraction were calculated by subtracting the annual attributable fraction in the last year with data from the annual attributable fraction in the first year with data, and absolute reductions in $PM_{2.5}$ and BC were calculated by subtracting the annual average concentrations in the last year with data from the annual average concentrations in the first year with data. The annual attributable fractions for cause-specific hospital admissions were calculated based on the exposure-response relationships with a theoretical minimal risk exposure level of 0 μg/m^3 as the reference concentration. Negative numbers in absolute reductions represent increases in air pollution concentrations and attributable fractions over the study period. Deeper color presents a larger decline. Cities in gray were not included in the analyses because no hospital admission data were available during the study period.

bring more health benefits than $PM_{2.5}$ after the implementation of the APPCAP in China. Regionally, reductions in city-specific annual attributable fractions increased significantly along with greater reductions in BC in Northwest China, whereas there was no similar increasing trend observed for $PM_{2.5}$. This may be because sandstorms and coal consumption make sulfate the most abundant water-soluble constituent in $PM_{2.5}$ in Northwest China[44,45], and our findings suggested that sulfate was not independently associated with cause-specific hospital admissions in models with adjustment for BC. The high proportion of sulfate in $PM_{2.5}$ (24.14% in Northwest China versus the nationwide average of 21.98%) may dilute the health benefits of reductions in $PM_{2.5}$ in cities located in Northwest China. This finding highlights the importance of prioritizing BC as a key $PM_{2.5}$ constituent in future air pollution control policies to achieve more substantial health benefits.

The deleterious impact of BC may be explained by the small size (generally 0.1-1 μm), absorbability of solar radiation, and strong adsorption capacity of BC, which make it easily internalized by alveolar macrophages and subsequently trigger inflammatory storms in the pulmonary and circulatory systems[46,47]. BC is also shown to increase the frequency of ST-segment depression events (an indicator for myocardial ischemia) in electrocardiogram and heart rate and result in cardiac autonomic dysfunction[48]. Meanwhile, BC can be directly transferred into the brain through the "lung-to-brain" pathway or olfactory neurons and can also reach distant organs, such as the kidney, through systemic circulation[49,50].

Our study has several strengths. Our study used real-world exposure-response relationships to quantify the potential health benefits related to reduced fine-particulate air pollution on a $PM_{2.5}$ constituent-specific and morbidity cause-specific basis at the nationwide level. Furthermore, by panoramically presenting the health co-benefits of APPCAP on cause-specific hospital admissions, our study highlights the substantial impacts of fine-particulate air pollution on disease outcomes across multiple organ systems, offering a broad perspective on the wide-ranging health advantages of air pollution control measures. Third, the study utilized a national medical insurance database with extensive geographic coverage and good representativeness of the urban population in China[51,52].

The study has several limitations. Due to the reform of health administration institutions in China (marked by the establishment of the National Healthcare Security Administration) in 2018 (ref. 53), we could not access updated medical insurance data on and after 2018 and extend the timeline beyond 2017. Moreover, due to the nature of the city-specific (instead of individual-specific) health information and ethical concerns in such a large-scale study, the data were anonymized without individual identifiers and analyzed at the city level. Thus, it was unable to distinguish first-time admissions and readmissions or obtain individual-level information (such as migration). The city-level average exposure used in this study may also lead to potential misclassification of exposure. However, the use of city-level exposure data conforms to practices of air pollution control policies and the development of public health intervention strategies (for example, health alerts). Furthermore, unavoidable diagnostic errors of cause-specific hospital admissions may introduce misclassification bias, which typically reduces the precision and bias the effect estimates to null[54]. Finally, the study lacked data from the rural population, and the generalizability of our findings needs to be interpreted with caution.

In conclusion, through a nationwide case-crossover analysis in China, our study demonstrates that air-quality improvements as shown by reduced fine-particulate air pollution after the implementation of the clean-air policies were accompanied by wide-ranging health benefits. Particularly, BC was identified as the leading $PM_{2.5}$ constituent that could be considered as a potential priority constituent in future air pollution control actions to obtain more substantial health benefits. Our findings emphasize the health co-benefits of stringent air pollution control policies implemented at a nationwide scale. In addition, it is necessary to develop air-quality guidelines for specific $PM_{2.5}$ constituents, particularly BC, to facilitate precision air pollution control and further reduce related disease burden in the future.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41591-025-03515-y.

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Methods

Data collection

In this study, we obtained city-specific hospital admission data from two major national medical insurance systems in China from 2013 to 2017—the urban employee-based basic medical insurance scheme (UEBMI) and the urban resident-based basic medical insurance scheme (URBMI), as described previously[55]. Briefly, the UEBMI covers urban employees and those retired, with main funding sourced from payroll taxes. URBMI covers urban residents, including children, students, elderly people without previous employment, and the unemployed, with governmental subsidies as the main funding sources. The national medical insurance database covers all levels of healthcare facilities and has good coverage of the urban population without sociodemographic inequality in China[51,52]. Citizens shall, in accordance with applicable laws, have the right to receive basic medical and healthcare services from the state and society[51]. Unlike developed countries, such as the United Kingdom, commercial medical insurance is underdeveloped in China, and it often serves as supplementary to the basic medical insurance[56]. The basic medical insurance scheme is featured as wide coverage and affordable for the entire urban population to obtain fundamental health services. Basic medical insurance does not intend to provide services for certain subpopulations, instead it is subsidized by the government and funded through mandatory means to the entire general population. It was estimated that by 2014, China's universal basic medical insurance systems had covered 97.5% of the entire population[57]. Building on our previous work[4,55], we have further updated the database and included more cities with hospital admission records with further approvals from relevant data management agencies.

Generally, the principal discharge diagnosis for each beneficiary was recorded by the doctor and submitted to a centralized medical insurance system to claim reimbursements in the settlement of medical expenses[5]. Cause-specific hospital admissions were identified based on the principal discharge diagnosis and were categorized into the following 10 major causes based on the codes of the International Classification of Diseases, 10th Revision (ICD-10) and text: respiratory diseases (including asthma and lower respiratory infections), CVDs (including cardiac arrhythmias, CHD, heart failure, and stroke), mental and neurological diseases (including depression, schizophrenia, and Parkinson's disease), and kidney disease (including CKD). These diseases were chosen based on previous evidence of a potential relationship with $PM_{2.5}$[4,5,58–60] and also the data availability from the UEBMI and the URBMI. The detailed ICD-10 codes for cause-specific hospital admissions are presented in Supplementary Table 14. Identifiable individual information, such as name and national ID number, was unavailable for analysis due to the personal privacy protection policy, but daily cause-specific hospital admission number was aggregated based on the number of admission records with unique ID at the city level before data desensitization. For each cause-specific hospital admission outcome, cities with total hospital admission records of fewer than 50 cases during the study period were excluded from the analyses to ensure adequate statistical power. We finally included a total of 292 cities of prefecture level or above (out of 338 such cities in total in 2017) in China that encompassed all health outcomes of interest, covering 699 million urban population (85.93% of the total urban population in China) at the end of 2017. Detailed information on cause-specific hospital admissions is presented in Supplementary Table 15.

Ethics approval

This study was exempted from institutional review board approval by the Biomedical Ethics Committee of the Health Science Center of Xi'an Jiaotong University because no data with any individual identifiers were extracted for this study.

Exposure assessment

Daily average concentrations of $PM_{2.5}$ and its major constituents (including BC, sulfate, nitrate, ammonium, chloride and OM) from 2013 to 2017 were obtained from the ChinaHighAirPollutants (CHAP) database with a high spatial resolution (1 × 1 km), which has been widely used in previous studies[58,61]. By considering the complex relationships between $PM_{2.5}$ sources and changes in its chemical constituents, the CHAP adopted a new simulation method called four-dimensional spatiotemporal deep forest (4D-STDF) model, which takes advantage of multiple tree-based machine learning models, to construct robust nonlinear relationships between each $PM_{2.5}$ constituent and the $PM_{2.5}$ total mass concentration[62]. The cross-validation R^2 values with the ground-based observations of BC, sulfate, nitrate, ammonium and chloride were 0.82, 0.74, 0.75, 0.71 and 0.66, respectively, and the average root-mean-square errors were 1.64 μg/m^3, 5.99 μg/m^3, 6.61 μg/m^3, 4.29 μg/m^3 and 2.30 μg/m^3, respectively[62]. We further compared $PM_{2.5}$ from the CHAP dataset and $PM_{2.5}$ from the China National Urban Air Quality Real-time Publishing Platform (https://air.cnemc.cn:18007/). The Spearman correlation coefficient and the intraclass correlation coefficient were 0.871 and 0.837, respectively, suggesting high consistency between the two datasets (Supplementary Table 16). Spearman's correlation coefficients between $PM_{2.5}$, major $PM_{2.5}$ constituents, and meteorological factors in 292 Chinese cities of prefecture level or above during 2013-2017 are shown in Supplementary Table 17. OM was calculated as $PM_{2.5}$ total mass minus BC, sulfate, nitrate, ammonium, and chloride in the study[63].

For each city included in the present study, daily average concentrations of $PM_{2.5}$ and its constituents were calculated by aggregating the concentrations of the grid cells within each city's boundary. Additionally, daily average temperature and relative humidity between 1 January 2013 and 31 December 2017 for the included cities were obtained from the China Meteorological Data Sharing Service System (http://data.cma.cn/) by averaging the available monitoring sites in each city.

Statistical analysis

First, we applied a two-stage time-stratified case-crossover analytical framework to explore the city-specific and overall associations between short-term exposures to $PM_{2.5}$ and its major constituents with cause-specific hospital admissions, which were further used to quantify the health benefits attributable to reduced fine-particulate air pollution.

In the first stage, case day was defined as the date of cause-specific hospital admission, and the other 3 or 4 days in the same stratum were defined as the control days. For each cause-specific hospital admission outcome in each city, we created a case-crossover dataset and applied a conditional logistic regression model adjusting for a binary indicator for public holidays and natural cubic splines with six and three degrees of freedom for moving averages of daily average temperature and relative humidity of the present day and previous 21 days, respectively[64,65]. As shown in Supplementary Table 18, this time window selected for temperature and relative humidity was generally applied to the multiple cause-specific hospital admissions based on previous literature and model Bayesian information criterion. For $PM_{2.5}$ and its major constituents, the 2-day moving average of the present day and previous day (lag01) was selected as the main time window[66].

In the second stage, we used random-effects models to pool the city-specific estimates (associated with a 1 μg/m^3 increase in $PM_{2.5}$ and its constituents) and then transformed the pooled estimates into an IQR scale. We constructed three models to test the robustness of the effect estimates: the basic single-constituent model incorporating $PM_{2.5}$ constituents in the model one at a time; the constituent residual model testing the independent associations of $PM_{2.5}$ constituents with cause-specific hospital admissions; and the remaining $PM_{2.5}$ mass-adjusted model with $PM_{2.5}$ total mass minus the constituent being included in the model. Given the strong correlations between certain constituents and $PM_{2.5}$ total mass (Supplementary Table 17), we refrained from establishing a constituent-$PM_{2.5}$ joint model to avoid underestimating the potential effect of a specific constituent[67]. To address the multiple testing issue for a given constituent, 10 and 24 *P* values for major cause-specific hospital admissions and their included subtypes were treated as a batch and adjusted together through the Benjamini-Hochberg procedure to correct the *P* values[68]. Corrected *P* values < 0.05 were considered statistically significant, keeping the false discovery rate < 5%.

The attributable fractions for major cause-specific hospital admissions were calculated based on the exposure-response relationships with a theoretical minimal risk exposure level of 0 μg/m^3 as the reference concentration (considering the absence of evidence for an exposure threshold below which effects on hospital admissions are not observed). The attributable fractions for cause-specific hospital admissions associated with $PM_{2.5}$ and its major constituents were calculated as follows[69]:

$$\mathrm{AN_{dic}} = \frac{e^{\{\log RR_d \times X_{ic}\}} - 1}{e^{\{\log RR_d \times X_{ic}\}}} \mathrm{N_{dic}}$$

$$\mathrm{AF_{di}}\% = \frac{\Sigma_{\{c=1\}}^{m} AN_{dic}}{\mathrm{F_{\{total\_di\}}}} \times 100\%,$$

where AN_{dic} denotes the number of daily hospital admissions for disease d attributable to daily $PM_{2.5}$ or its major constituents on day i of city c; RR_d indicates the relative risk (RR) of hospital admissions for disease d associated with each 1 μg/m^3 increase in $PM_{2.5}$ or its major constituents generated from the basic single-constituent model. X_{ic} is the absolute concentration difference between the concentration of $PM_{2.5}$ or its major constituents at lag01 on day i of city c and the reference concentration of 0 μg/m^3; N_{dic} indicates the number of daily hospital admissions for disease d on day i of city c; $AF_{di}\%$ denotes the attributable fraction of hospital admissions for disease d on day i; m presents the total number of the included cities; and $F_{\{total\_di\}}$ is the total number of hospital admissions for disease d on day i in the included cities. Annual attributable number was calculated by aggregating the daily attributable number within each year. Annual attributable fraction was calculated by annual attributable number divided by the annual total number of hospital admissions for disease d in the included cities. The upper and lower 95% CI values of the pooled RR were used to calculate the 95% CIs of attributable number and attributable fraction using the above equations.

Compared with the annual attributable fraction in 2013, the absolute reduction in annual attributable fraction in 2017 was calculated by subtracting the annual attributable fraction in 2017 from the annual attributable fraction in 2013. The relative reduction was calculated by dividing the absolute reduction in annual attributable fraction in 2017 (with reference to the annual attributable fraction in 2013) by the annual attributable fraction in 2013. To test the robustness of the results, we also restricted the analysis to cities with 5-year data on hospital admissions in the sensitivity analysis. City-specific annual attributable fractions were averaged for nine major cause-specific hospital admissions with significant associations with $PM_{2.5}$ and BC. Scatter plots based on linear regression analyses were used to visualize the correlations between city-specific absolute reductions in fine-particulate air pollution and absolute reductions in annual attributable fractions at both the nationwide level and regional levels (categorized into North China, Central China, Northwest China, Northeast China, East China, Southwest China and South China according to the standard geographic classification in China)[70]. Three sets of outlier cities were identified as follows: (1) cities with large reductions in annual attributable fraction (defined as studentized residual larger than 2) but small reductions in air pollution (defined as absolute reductions in $PM_{2.5}$ and BC smaller than the medians, which were 12.99 μg/m^3 and 0.54 μg/m^3 for $PM_{2.5}$ and BC, respectively) in 2017 compared with 2013; (2) cities with increases in annual attributable fraction despite air pollution reduced in 2017 compared with 2013; and (3) cities with large reductions in air pollution (defined as hat statistic greater than twice of the average hat value) but small reductions in annual attributable fraction (defined as absolute reductions in annual attributable fraction smaller than the medians, which were 0.72% and 0.80% for $PM_{2.5}$ and BC, respectively) in 2017 compared with 2013.

The annual absolute declining rates of attributable fractions and average concentrations of $PM_{2.5}$ and its major constituents were estimated and tested by the Theil-Sen median slope estimator, a non-parametric statistical method used to identify time-series trends by collecting the slopes of all pairs of points and finding the median of these slopes, along with the Mann-Kendall test[71]. To calculate the total avoided numbers, we first estimated the annual absolute declining rates of $PM_{2.5}$ and BC concentrations during 2013–2017 using the Theil-Sen median slope estimator, and then the following equation was used to estimate the total avoided numbers of different cause-specific hospital admissions attributable to such annual absolute declining rates[72]:

$$H_d = \sum_{t=1}^{4} (\exp(\beta \times \Delta x \times t) - 1) \times N_{d(2013+t)},$$

where H_d is the total avoided numbers of hospital admissions for disease d; β is the national pooled risk estimated for a 1 μg/m^3 change in $PM_{2.5}$ or BC; Δx represents the annual absolute declining rate (4.23 μg/m^3 per year for $PM_{2.5}$ and 0.17 μg/m^3 per year for BC); t is the year of the sample and $N_{d(2013+t)}$ is the total number of hospital admissions for disease d in the year 2013 + t. Because 2013 is the baseline year, there is a total of 4 years (2014-2017) with reduced fine-particulate air pollution compared with 2013, and thus the range for t is 1 to 4.

As the associations between $PM_{2.5}$ and BC and cause-specific hospital admissions were the basis for calculating health benefits indicated by annual attributable fractions, we conducted several sensitivity analyses to test the robustness of the associations: (1) explored the potential effects of $PM_{2.5}$ and its major constituents at additional lags using the basic single-constituent model, including the present day (lag0), the previous one day (lag1) and previous two days (lag2); (2) included natural cubic splines of temperature and relative humidity at shorter lags (moving averages of the present day and previous 7 days or the present day and previous 14 days) with six and three degrees of freedom, respectively; (3) restricted the analysis to cities with 5-year data from 2013 to 2017; (4) additionally adjusted for time spline for day of the year with seven degrees of freedom in the single-constituent model to account for within-month trends; (5) used symmetric bidirectional matching strategy within a narrower window of 14 days to account for the pronounced seasonality in hospital admissions[73] (that is, control days were selected 7 days before and after the case days); (6) additionally adjusted for ozone in the basic single-constituent model[27]; and (7) conducted a two-constituent model analysis with two constituents simultaneously included in one single model.

By considering the proportion of urban and rural residents in the included cities, we obtained the city-specific total numbers of urban and rural residents in 2017 from the City Statistical Yearbook and calculated the city-specific proportions of urban residents. Because the distribution of the city-specific proportions of urban residents was skewed, we chose the median city-specific proportion of urban residents (52%) to categorize cities with a majority of urban residents (denoted as "_U" in Supplementary Table 6) and a majority of rural residents (denoted as "_R" in Supplementary Table 6). The differences between the effect estimates of the two subgroups were tested by the two-sample Z test, and the false discovery rate was used to adjust for multiple comparisons.

All statistical analyses were performed using R Software, version 4.0.3. The *survival* package was used for conditional logistic regression analysis, the *metafor* package was used to build the random-effect models, and the *wql* package was used to conduct the Theil-Sen median slope estimator along with the Mann-Kendall test. A two-sided *P* value < 0.05 was considered statistically significant.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Air pollution data used in this study can be applied from the China-HighAirPollutants (CHAP) at https://weijing-rs.github.io/product.html. Meteorological data are available from the China Meteorological Data Sharing Service System at http://data.cma.cn/. The basemaps used in Figs. 1 and 4 and Extended Data Fig. 1 are from GaryBikini/ChinaAdminDivisonSHP: v24.02.06, 2024 (doi:10.5281/zenodo.10624971). The medical insurance data analyzed in this study are regulated by governmental policies and cannot be made available to the public for ethical and privacy reasons. Health data used in this study are available under restricted access due to the identifiable nature of the data and compliance with data use agreements. Application for collaborative research purposes based on the data used in the study can be addressed by contacting the corresponding authors. The request will be answered within 12 weeks.

Code availability

The statistical code for the main analyses can be found at: https://github.com/hmliu123/Case-crossover-study-constituents-hospital-admission-.git.

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Author contributions

S.W. and Y. Liu are joint corresponding authors and provide supervision for this work. H.L. and J.L. are joint first authors with equal contributions. S.W. conceptualized the study framework and designed the analytic strategies. H.L. and J.L. analyzed and verified the data. H.L. and J.L. wrote the original draft. X.C. and J. Wei assisted with the data processing of the exposure data. J. Wang, C.W., and Y. Li assisted in the data extraction and cleaning of the hospital admission data. S.W. and Y. Liu are the study guarantors. All authors participated in the interpretation of the data and critical review of the paper, read the final version of the paper, and approved the paper for submission.

Competing interests

All authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41591-025-03515-y.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41591-025-03515-y.

Correspondence and requests for materials should be addressed to Yuewei Liu or Shaowei Wu.

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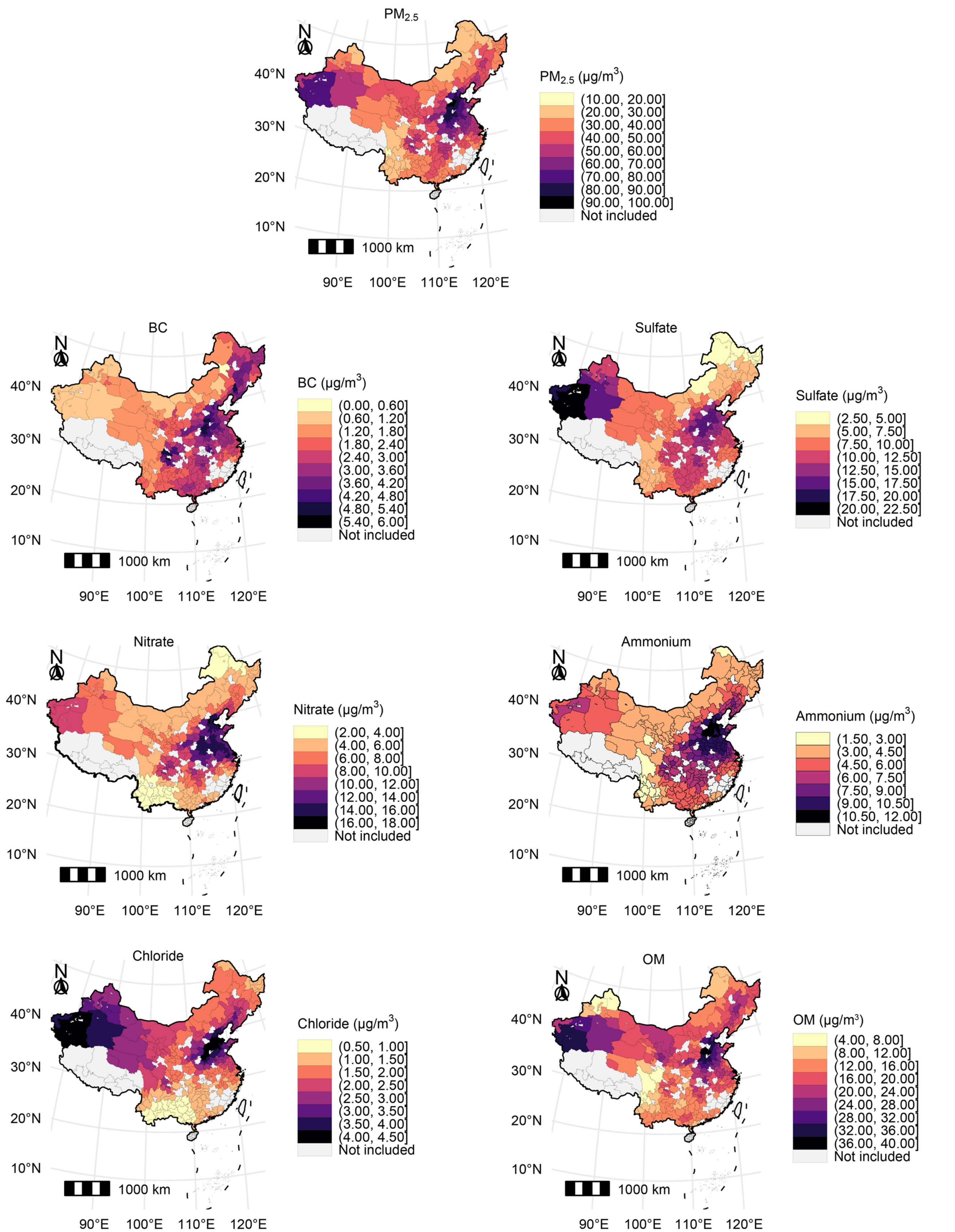
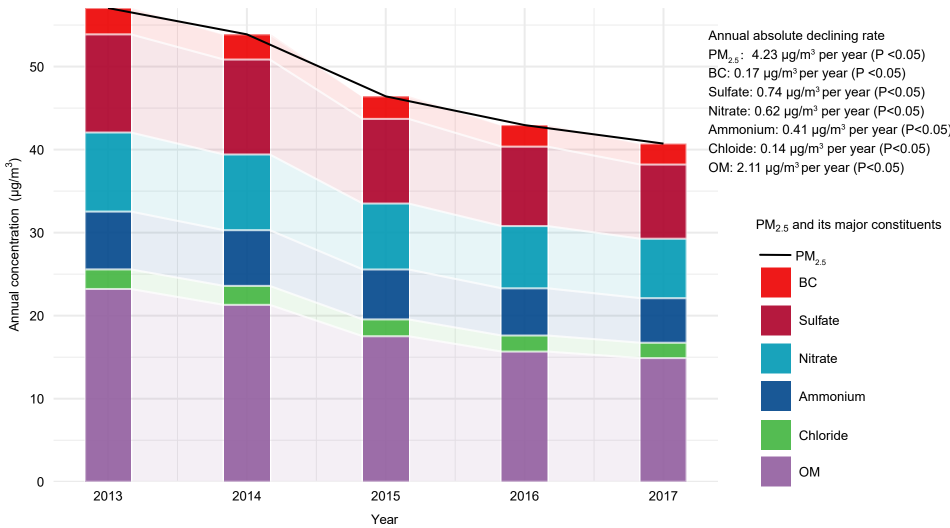


Extended Data Fig. 1 | Spatial distribution of city-specific annual average concentrations of ambient $PM_{2.5}$ and its major constituents in 292 Chinese cities of prefecture level or above during 2013-2017. Deeper color presents a higher concentration. Cities in gray were not included in the analyses because no hospital admission data were available during the study period. Abbreviations: BC, black carbon; OM, organic matter; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm or less.

https://doi.org/10.1038/s41591-025-03515-y



Extended Data Fig. 2 | Annual average concentrations of ambient $PM_{2.5}$ and its major constituents in 292 Chinese cities of prefecture level or above during 2013-2017. The solid line represents the annual average concentration of $PM_{2.5}$ in 292 Chinese cities of prefecture level or above during 2013-2017. Annual absolute declining rates (μg/m^3 per year) of $PM_{2.5}$ and its major constituents were estimated and tested by the Theil-Sen median slope estimator along with the Mann-Kendall test. Abbreviations: BC, black carbon; OM, organic matter; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm or less.

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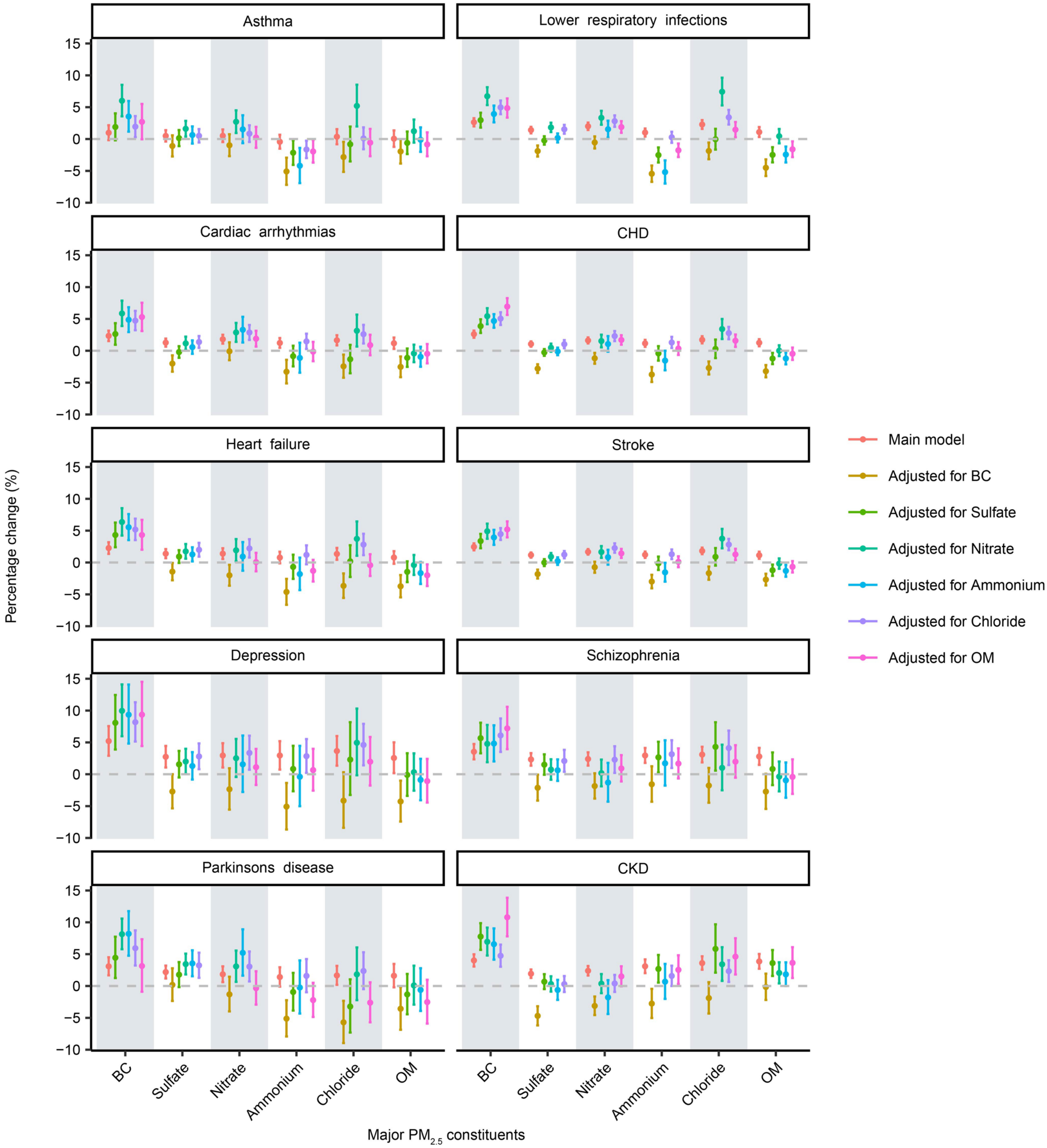

Extended Data Fig. 3 | Overall percent changes with 95% confidence intervals in risks of major cause-specific hospital admissions associated with each IQR increase in major $PM_{2.5}$ constituents at lag01 based on the two-constituent model. Supplementary Table 15 shows the summary admission numbers for different cause-specific hospital admissions during the study period. Overall n = 48,623,468. Points represent estimates of percent changes in risks of major cause-specific hospital admissions associated with each IQR increase in major $PM_{2.5}$ constituents. Error bars represent 95% CIs of the percent changes. Each line connecting the error bars represents the range of overall percent change values. Abbreviations: BC, black carbon; CHD, coronary heart disease; CI, confidence interval; CKD, chronic kidney disease; IQR, interquartile range; OM, organic matter; $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm or less.

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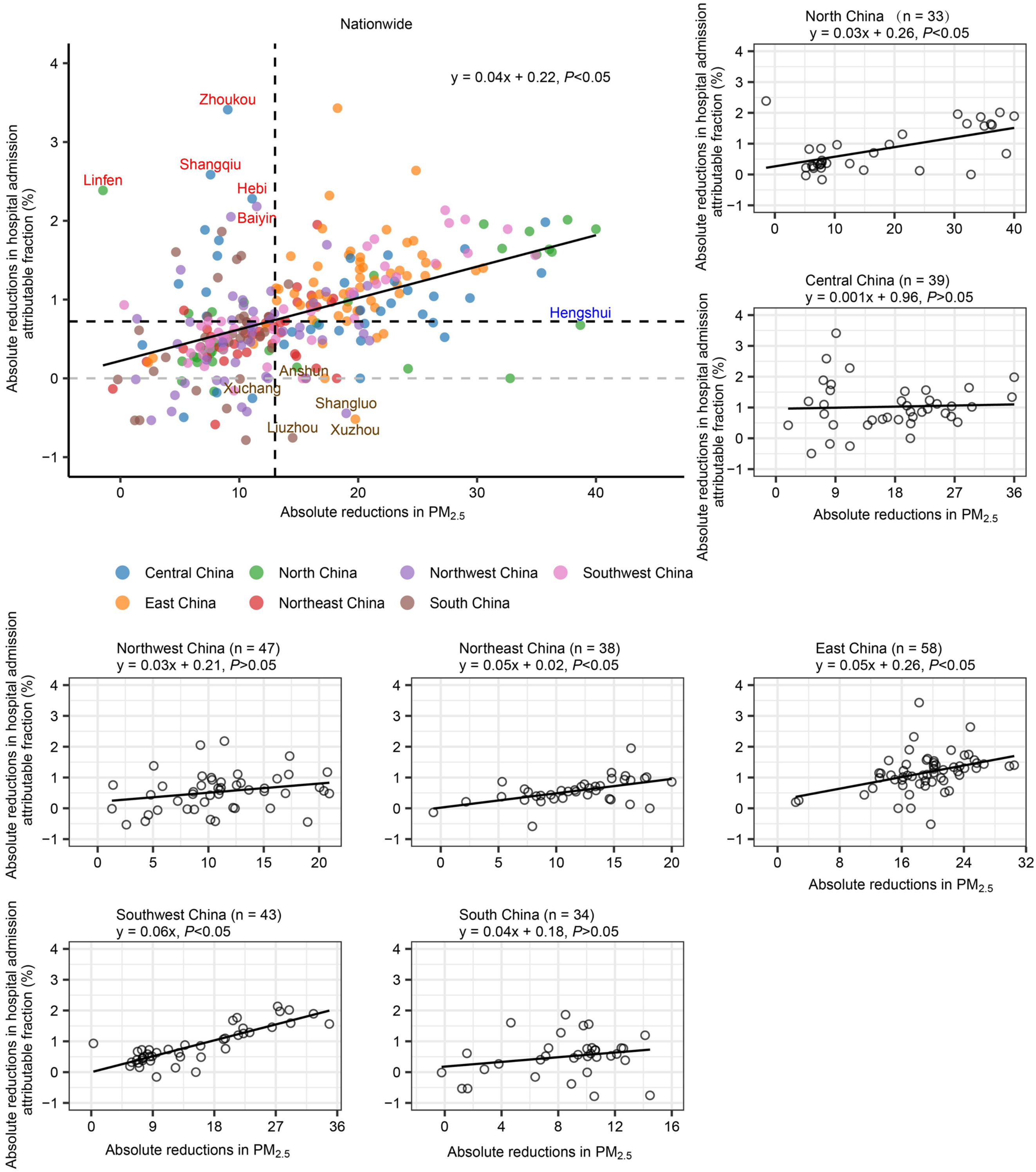

Extended Data Fig. 4 | See next page for caption.

https://doi.org/10.1038/s41591-025-03515-y

Extended Data Fig. 4 | Scatter plots of city-specific absolute reductions in ambient $PM_{2.5}$ and average annual hospital admission attributable fraction of nine major cause-specific hospital admissions from 2013 to 2017 at the nationwide and regional levels. City-specific annual attributable fractions were averaged for nine major cause-specific hospital admissions with significant associations with $PM_{2.5}$. For cities with data fewer than 5 years (the number of cities with data fewer than 5 years ranged from 54 for depression to 87 for heart failure), absolute reduction in annual hospital admission attributable fraction was calculated by subtracting the annual attributable fraction in the last year with hospital admission data from the first year with hospital admission data, and absolute reduction in annual average $PM_{2.5}$ concentration was calculated by subtracting the annual average concentration in the last year with hospital admission data from the first year with hospital admission data. The names of cities shown in red indicate 5 cities with the largest reductions in annual hospital admission attributable fraction but small reductions in air pollution. The names of cities shown in brown indicate 5 cities with the most apparent increases in annual hospital admission attributable fraction despite $PM_{2.5}$ concentrations reduced during the study period. The name of city shown in blue represents the city (Hengshui) with a large reduction in air pollution but a small reduction in annual hospital admission attributable fraction. Negative numbers represent increases in air pollution concentrations and attributable fractions. The black solid line in each figure panel represents the linear regression line. The gray horizontal dashed line in the nationwide figure panel represents absolute reductions in annual hospital admission attributable fraction equal to zero, meaning no change in annual attributable fraction from 2013 to 2017. The black vertical and horizontal dashed lines in the nationwide figure panel represent the median values for city-specific absolute reductions in $PM_{2.5}$ and the average annual attributable fractions of nine cause-specific hospital admissions associated with ambient $PM_{2.5}$ in 292 cities, respectively. Abbreviation: $PM_{2.5}$, particulate matter with an aerodynamic diameter of 2.5 μm or less.

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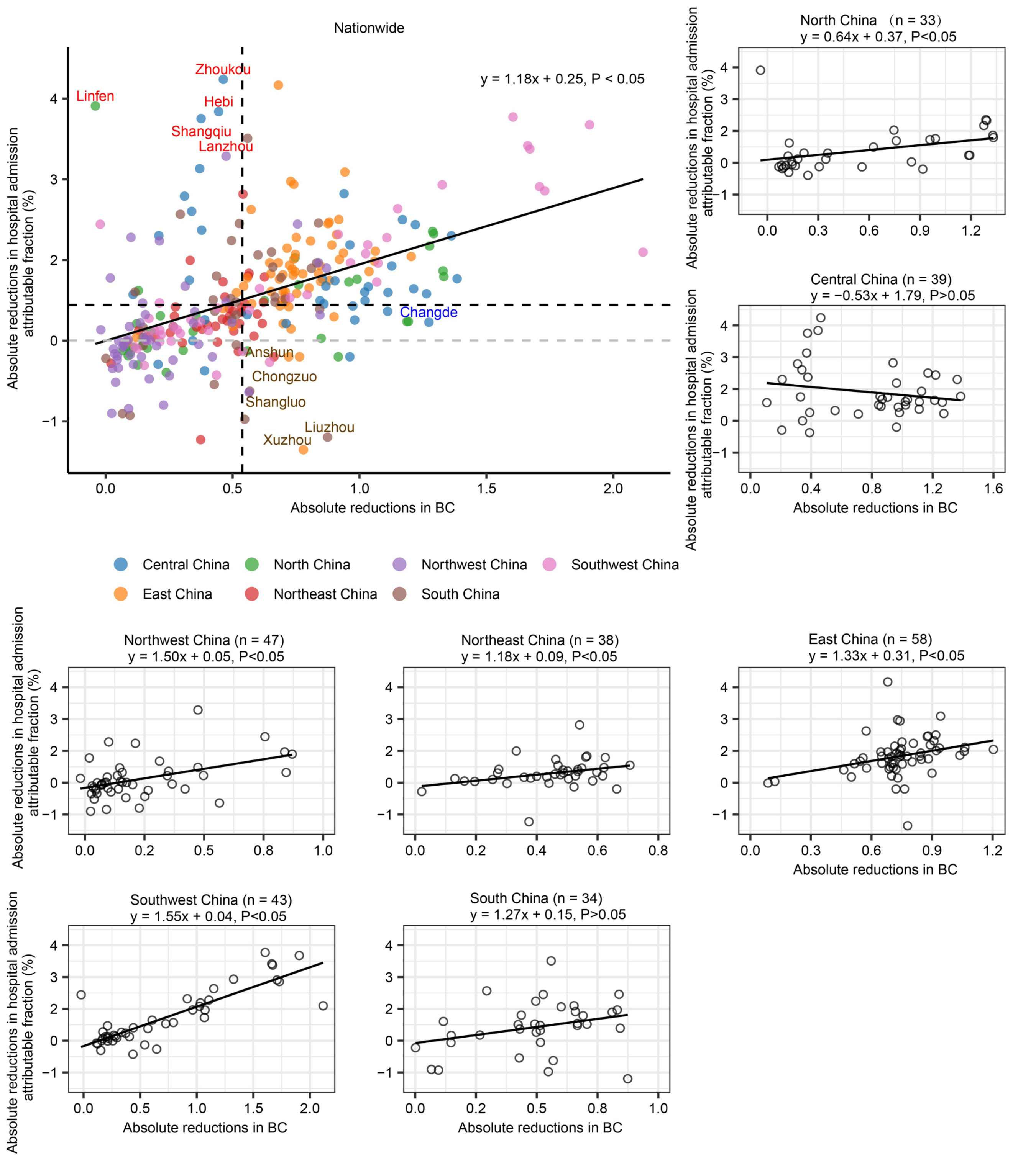

Extended Data Fig. 5 | See next page for caption.

https://doi.org/10.1038/s41591-025-03515-y

Extended Data Fig. 5 | Scatter plots of city-specific absolute reductions in black carbon and average annual hospital admission attributable fraction of nine major cause-specific hospital admissions from 2013 to 2017 at the nationwide and regional levels. City-specific annual attributable fractions were averaged for nine major cause-specific hospital admissions with significant associations with BC. For cities with data fewer than 5 years (the number of cities with data fewer than 5 years ranged from 54 for depression to 87 for heart failure), absolute reduction in annual hospital admission attributable fraction was calculated by subtracting the annual attributable fraction in the last year with hospital admission data from the first year with hospital admission data, and absolute reduction in annual average BC concentration was calculated by subtracting the annual average concentration in the last year with hospital admission data from the first year with hospital admission data. The names of cities shown in red indicate 5 cities with the largest reductions in annual hospital admission attributable fraction but small reductions in air pollution. The names of cities shown in brown indicate 5 cities with the most apparent increases in annual hospital admission attributable fraction despite $PM_{2.5}$ concentrations reduced during the study period. The name of city (Changde) shown in blue represents the city with a large reduction in air pollution but a small reduction in annual hospital admission attributable fraction. Negative numbers in absolute reductions represent increases in air pollution concentrations and attributable fractions. The black solid line in each figure panel represents the linear regression line. The gray horizontal dashed line in the nationwide figure panel represents absolute reductions in annual hospital admission attributable fraction equal to zero, meaning no change in annual attributable fraction from 2013 to 2017. The black vertical and horizontal dashed lines in the nationwide figure panel represent the median values for city-specific absolute reductions in BC and the average annual attributable fractions of nine cause-specific hospital admissions associated with BC in 292 cities, respectively. Abbreviation: BC, black carbon.

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Software and code

Policy information about availability of computer code

Data collection	Data collection was performed in R (V.4.0.3).
Data analysis	No commercial, open source or custom code was used to analyze the data in this study. This study did not generate new or customized code/ algorithm. We used the software Amap and R package "amapGeocode" (V.0.6.0) to get city-level exposures of PM2.5 and its major constituents. The conditional logistic regression models were fit using the "survival" R package (V.3.2.7). The city-specific associations were pooled in the random-effects model using the "metafor" R package (V.4.2.0). The "wql" R package (V.1.0.1) was used to conduct the Theil-Sen median slope estimator along with the Mann-Kendall test. Codes for the main statistical analyses are available from https://github.com/ hmliu123/Case-crossover-study-constituents-hospital-admission-.git.

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Air pollution data used in this study can be applied from the ChinaHighAirPollutants (CHAP) database at https://weijing-rs.github.io/product.html. Meteorological data are available from the China Meteorological Data Sharing Service System at http://data.cma.cn/. The health insurance data analyzed in this study are regulated by governmental policies and cannot be made available to the public due to ethical and privacy reasons. Health data used in this study are available under restricted access due to the identifiable nature of the data and compliance with data use agreements. Application for collaborative research purposes based on the data used in the study can be addressed by contacting the corresponding authors. The request will be answered within 12 weeks.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	Results of sex-based analyses were not performed.
Reporting on race, ethnicity, or other socially relevant groupings	In our case-crossover study, individual information on race, ethnicity or other socially relevant groupings were not available due to ethical/privacy reasons. Thus, we did not include these variables in our analysis.
Population characteristics	A total of 26,397,562 (54.29%) males and 22,225,906 (45.71%) females were included in the analysis. In addition, 4,625,544 (9.51%) aged 14 years or below, 3,092,842 (6.36%) aged 15-39, 16,888,769 (34.73%) aged 40-64, 11,225,285 (23.09%) aged 65-74, and 12,791,082 (26.31%) aged 75 years or above.
Recruitment	Individuals who were admitted to hospital admissions through the urban employee-based basic medical insurance scheme (UEBMI) and the urban resident-based basic medical insurance scheme (URBMI) during 2013-2017 were included. Data on daily hospital admission numbers at city level were used in the study.
Ethics oversight	This study was exempted from institutional review board approval by the Biomedical Ethics Committee of Health Science Center of Xi'an Jiaotong University because no data with any individual identifiers were extracted for this study.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

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Study description	We conducted a two-stage time stratified case-crossover study using quantitative data of city-level hospital admission records from two major Chinese medical insurance systems in 292 Chinese cities during 2013-2017 to analyze the health benefits attributable to reduced air pollution. Exposure-response relationships were identified by conditional logistic models, which were used to quantify the fractions of cause-specific hospital admissions attributable to short-term exposure to PM2.5 and its major constituents. Hospital admission benefits attributable to reduced air pollution after the implementation of clean-air policies in China were quantified by reductions in annual attributable fraction. The trends of annual hospital admission attributable fractions and air pollution concentrations were quantified and tested by the Theil-Sen median slope estimator along with the Mann-Kendall test.
Research sample	City-specific hospital admission data were obtained from two major national health insurance systems in China from 2013 to 2017. Specifically, the UEBMI covers employees and those retired, and the URBMI covers residents (including children, students, and elderly people) without previous employment and the unemployed in the urban area. We finally included a total of 292 Chinese cities of prefecture-level or above (out of 338 such cities in total in 2017), covering 699 million urban population (85.93% of the total urban population in China in 2017). In our study, 48,623,468 hospital admissions that encompassed all health outcomes were included in the analyses, among which 26,397,562 (54.29%) were males, 22,225,906 (45.71%) were females, 4,625,544 (9.51%) aged 14 years or below, 3,092,842 (6.36%) aged 15-39, 16,888,769 (34.73%) aged 40-64, 11,225,285 (23.09%) aged 65-74, and 12,791,082 (26.31%) aged 75 years or above.

Sampling strategy	All available hospital admission data for the diseases involved from the UEBMI and URBMI in the 292 Chinese cities were included in the analysis. No sampling was done.
Data collection	Daily cause-specific hospital admissions were collected by administrative agencies of the Chinese government. The researchers were not blinded to the experimental condition or the study hypothesis.
Timing	The start date of data collection was 1st January 2013, and the end date was 31st December 2017.
Data exclusions	For each cause-specific hospital admission outcome, cities with fewer than 50 admission records during the study period were excluded from the analyses to ensure adequate statistical power.
Non-participation	Rural residents and urban residents without medical insurance coverage were not included in the study.
Randomization	There was no randomization in this observational study. The models were conditioned on strata defined by day of the week, month and year, which offered strong control for seasonality and secular changes, and yielded inferences based on within-city short-term pollution variability.

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☒	☐ Plants

Methods

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Seed stocks	*Report on the source of all seed stocks or other plant material used. If applicable, state the seed stock centre and catalogue number. If plant specimens were collected from the field, describe the collection location, date and sampling procedures.*
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